**Course: Computer Science Module: 6006CEM Machine Learning and Related Applications**

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**Coventry GitHub Repository URL** or **Coventry OneDrive URL** (mandatory):

< <https://github.coventry.ac.uk/iftikhars/9789180-SI-s1>>

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# Introduction

## **Problem statement**: Suicide risk prediction - Classification problem

## Motivation:

In research from [Brådvik (2018, p. 1)](#Brådvik) the suicide mortality rate is 1.4 percent of all global deaths. Biological, psychological, clinical, social, and environmental variables all have a role in the development of suicide risk. Because several risk variables are involved in defining a person's risk of suicide, determining a person's risk of suicide is difficult. Using computer testing and genetic screening, for example, to improve suicide risk assessment is a topic of continuing study [(Turecki et al., 2019, pp. 1)](#Turecki). To lower the number of suicide fatalities, prevention is essential [(Turecki et al., 2019, pp. 1)](#Turecki). This project aims to predict the risk factor of a person committing suicide so it could be prevented using a machine learning model.

## Related work

Previous work on risk suicide detection was looked at when choosing the dataset. The Study from [(NIROOMAND, 2020)](#Niroomand_work) carries a similarity to this study in that both studies focus on using classification machine learning algorithms to investigate probable factors that may raise the probability of suicide in people and try to predict the risk of suicide by using the same dataset. Both their study and this one use the same machine learning algorithms except logistic regression to determine the required outcome.

This research determines the best algorithms to use from a selection of algorithms which are then further improved to predict the best results by hyperparameter optimization and feature scaling which was not done in the research performed by [(NIROOMAND, 2020)](#Niroomand_work). This study also uses multiclass classification rather than binary classification.

# Analysis and pre-processing

## Data analysis

The dataset used in this project was obtained from kaggle.com and it is called “suicidedataextrafestures” it was collected by the Kaggle user DORNA NIROOMAND [(Niroomand, 2019)](#Niroomand_data). The dataset has 26 columns containing 5 categorical and 21 continuous variables. The data is collected from the year 1985 to 2016 from 48 different countries. The data is from 2 sexes, male and female and 6 different age groups. There are 17 columns in the dataset with 15110 rows; the rest of the columns have rows of different lengths. Outliers and null values are present in the dataset.

The dataset used in this project is available online at: <https://www.kaggle.com/dornani/widandsuicide?select=suicidedataextrafestures.csv>

## Taking care of missing data and outliers

Firstly, the data frame is imported, columns with high nan values and columns with repeated information are removed. Nan values are again checked from the remaining column and are replaced using the mean of the 10 K nearest neighbours which were determined as the best course of action for this case after researching [(Maladkar, 2018)](#Maladkar). The index of the data frame is reset and then outliers are checked. An outlier can be kept, removed or winsorized using any method that could create a high bias [Yang and Berdine (2016, p. 52-56)](#Yang). Outliers can capture information that may be a vital part of the area of study (Frost, 2021). When removing outlines, it's best to look at how they affect the subject area [(Frost, 2021)](#Frost). After observation, it was determined that the outliers are providing valuable information [(see Appendix C)](#_Appendix_C) and hence they will not be removed or winsorized.

## Encoding and checking correlation

Now all columns of type objects containing categorical features are one hot encoded except the country column. A heat map is plotted (see Figure 1 Correlation matrix) so the highest correlated features can be identified and be assigned as a new data frame to a variable. They will be used later to test whether they improve the model’s performance or not.

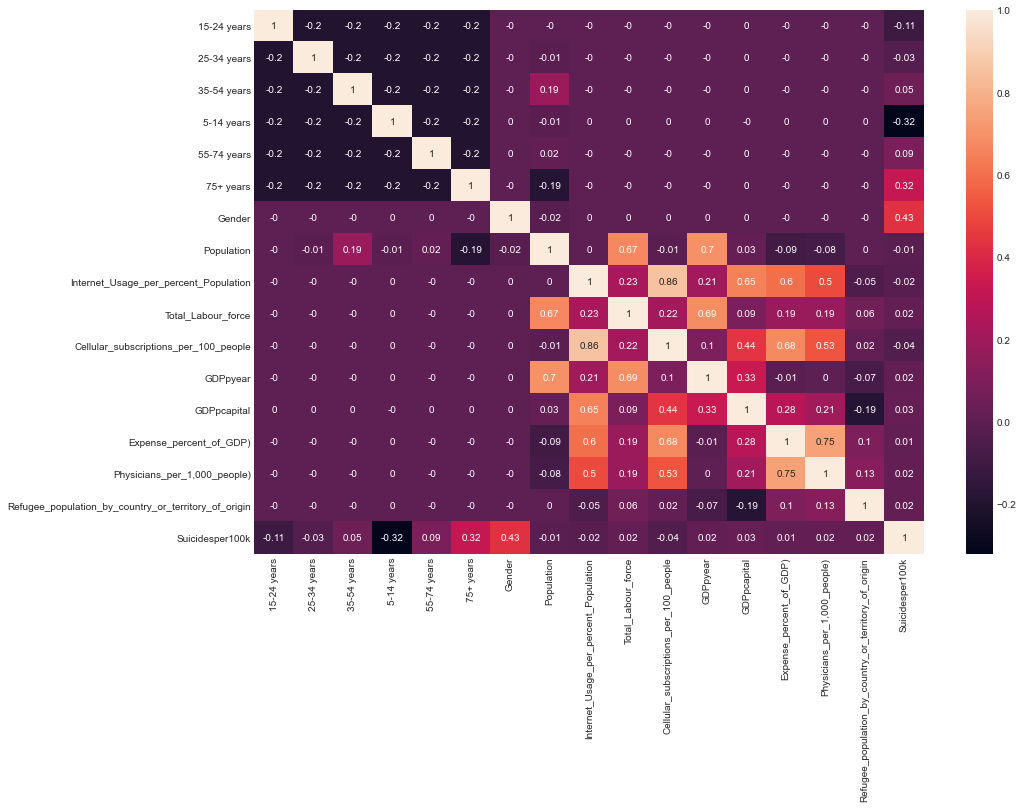


Figure 1 Correlation matrix

The country column is one hot encoded and after the encoding, there are a total of 64 columns in the dataset. Labels 1, 2, 3, 4, 5 are made using the sucidesper100k column. 1 being minimum risk, 2 being low risk, 3 being medium risk, 4 being high risk and 5 being a maximum risk for more on this [(see Appendix D)](#_Appendix_D). This was done so there are enough categories to model and the model is not too computationally heavy.

## Handling unbalanced data

The label samples are observed for each of the newly created label classes that will be used to perform oversampling. As it can be seen in (Figure 2 Label samples) that label samples are imbalanced. 1 having 9264 samples comprises 61.31% of the data, 2 having 2850 samples covers 18.86 % of the data 3 having 2177 samples covers 14.41 % of the data, 4 having 678 samples covers 4.49 % of the data and 5 having 141 samples covers 0.93 % of the total data in the label column suicideper100k.

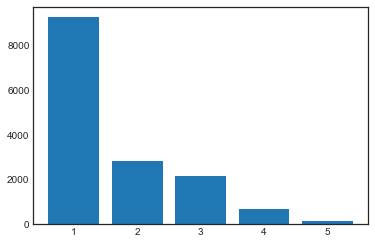


Figure 2 Label samples

## Applying PCA, feature section and splitting the data into training and testing sets

The features x and x2 are selected using the original dataset and the dataset obtained after using correlation respectively. The label y is used for both features. Principal component analysis is applied to all 9 continuous features in the dataset. PCA should not be applied to categorical data that has been one hot encoded or to data, not on the coordinate plane [(Walker, 2019)](#Walker). After applying PCA it was determined that the components could be reduced to 6 dimensions for above 90 % of data to be kept, so it was decided that PCA would not have a great impact on the model evaluation, and they were not utilized for model evaluation. An Oversampled label is selected y\_over so that results from the original features, features selected using correlation matrix and oversampled features, could be applied to different machine learning algorithms and the results could be evaluated. All these selected features are split into testing and training sets. It is split 80 % into the training and 20 % into the testing sets with the random state set to 1.

# Implementation

## Version control

Version control was implemented using Github throughout his project and it can be found online at: <https://github.coventry.ac.uk/iftikhars/9789180-SI-s1>

## Model selection

Supervised classification learning algorithms will be performed in this project. Cross-validation was performed on Logistic, KNN (K nearest neighbours), Naive Bayes, Neural Networks, Decision tree and Random Forest models. It was decided that the Decision Tree with a score of 93 %, Random forest scoring 94 % and KNN having a score of 71 % had the best cross-validated accuracy. These results can be observed in Figure 3 Model Selection and Figure 4 Model Selection. SVM and XGBoost were not used in this project because of hardware requirements and time constrains.

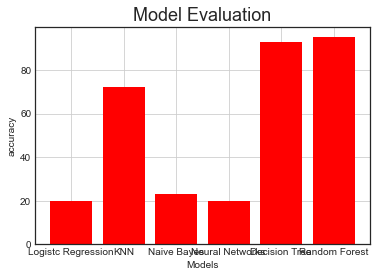


Figure 3 Model Selection

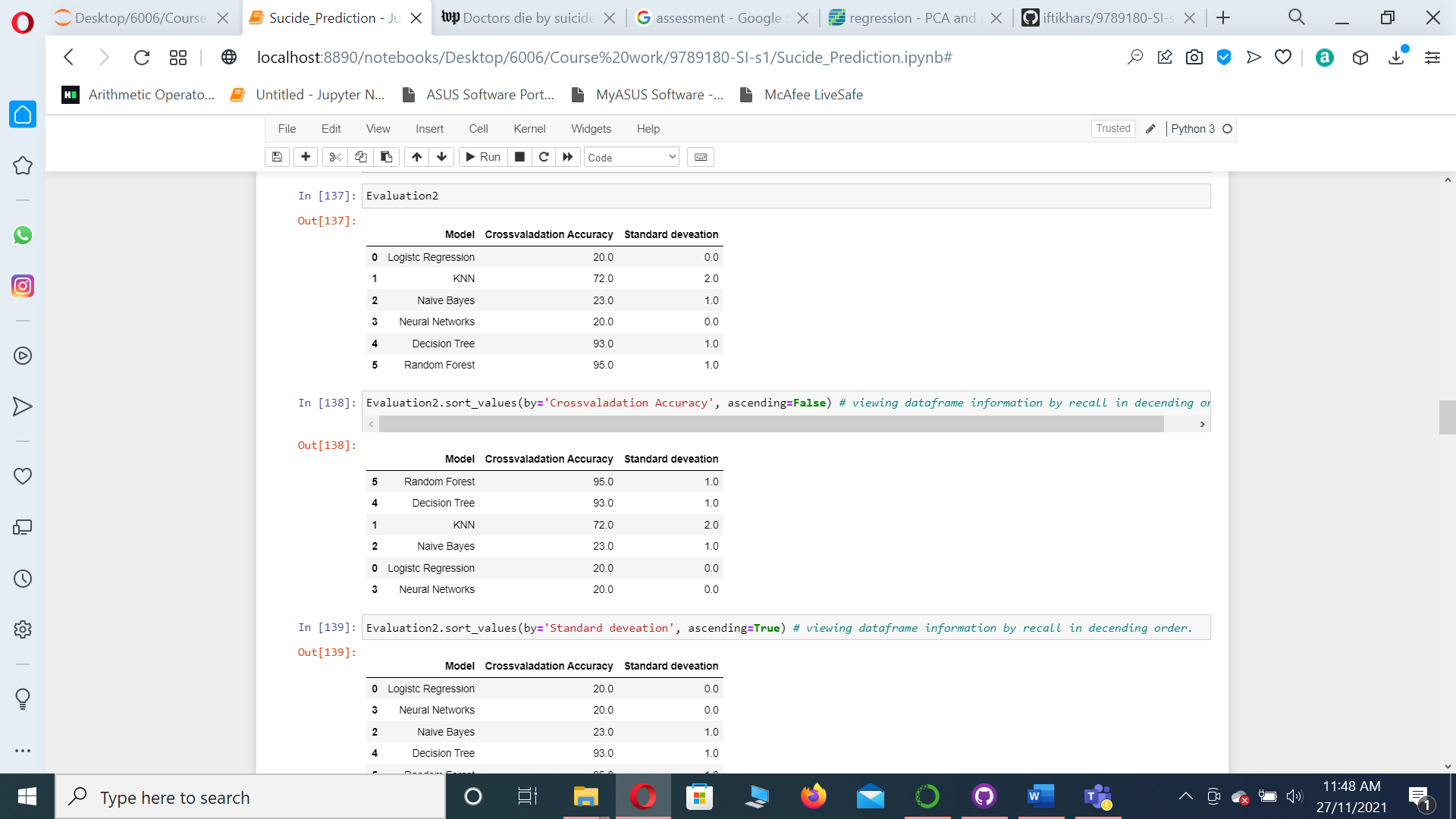


Figure 4 Model Selection

## Model optimization

Different hyperparameter optimization techniques were applied to the three selected models. They were applied using the following logic and order. First cross-validation was applied to narrow down on which hyperparameters give the best results individually, then random search and grid search was applied to a range of hyperparameters that had the most effect on increasing the accuracy of the model. Accuracy was chosen as a measure to optimize the hyperparameters as it was important how many correct predictions the model made for the test dataset.

After the hyperparameter selection. All the models were applied on all 3 feature variables X, X2 and X\_over and the continuous features of the X and X\_over variables were feature scaled using Standardscaler, MinMaxscaler, Robustscaler and Normaliser feature scaling techniques.

# Results and Evaluation

## KNN

KNN had the best testing and training set results with hyperparameters, 3 neighbours, weight set as distance using MinMaxScalar and it had similar overall scores using other scaling techniques, but the AUC (Area under the curve) was highest using the MinMaxScalar with 3 neighbours (see Figure 21 KNN MinMax3). When evaluated with cross-validation it performed best using 15 neighbours, weight set as distance with 80.22 % accuracy and 1.40 % standard deviation (see Appendix E).

## Random Forest

Random Forest had the best overall results on the testing and training sets with 1 min\_samples\_leaf, 2 min\_samples\_split, None max\_leaf\_nodes, 0.0 min\_weight\_fraction\_leaf, 'entropy' criterion, None max\_features, 121 max\_depth, 'random' splitter as hyperparameters score with MinMaxScalar and it had similar overall scores using other scaling techniques, but the AUC (Area under the curve) was highest using the MinMaxScalar (see Figure 46 Decision Tree MinMaxScalar). The defaults model results were 93.11 % with a 0.86 % standard deviation when evaluated with cross-validation (see Appendix E).

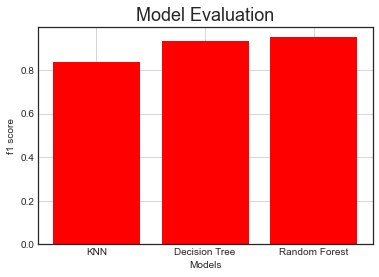
## Decision Tree

Decision Tree has the best overall results with 1 min\_samples\_leaf, 2 min\_samples\_split, None max\_leaf\_nodes, 0.0 min\_weight\_fraction\_leaf, 'entropy' criterion, None max\_features, 121 max\_depth, 'random' splitter as hyperparameters with MinMaxScalar (see Figure 46 Decision Tree MinMaxScalar ) has the best area under the curve. The defaults model results were 93.11 % with a 0.86 % standard deviation. The results after using MinMaxScaler with hyperparameter optimization were 94.44 % with a 1.05 standard deviation (see Appendix E).

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Because the algorithms are estimating people's probability of suicide, how many times they are predicted accurately is more significant than predicting anything positive, and how many times they were actually positive recall will be a top priority. It will not be the exclusive method of scoring since a model with 100% recall may always make a positive prediction; it would have 100% recall but be entirely useless as a result, the f1 score will be used to evaluate the model because it prioritises recall and accuracy equally. As seen in and Figure 5 f1 score the Random Forest model has the highest performance when predicting the f1 score with a mean f1 score of 0.950965 and the mean accuracy is 0.956131 with 10 cross-validations.

Figure 5 f1 score



Random Forest with hyperparameters 1 min\_samples\_leaf ,2 min\_samples\_split , None max\_leaf\_nodes , 0.0 min\_weight\_fraction\_leaf , 'entropy' criterion, None max\_features, 121 max\_depth, 'random' splitter gave 0.956131 accuracy, 0.961529 precision, 0.954255 recall, 0.950965 f1 score and 0.998497 Area under the curve when run with 10 cross-validations using on oversampled labels and features scaled using MinMaxScalar. When subtracting the standard deviation from (Figure 6 Overall model results) the Random Forest model gives 0.9448089 accuracy, 0.953715 precision, 0.931089 recall, 0.937287 f1 score and 0.997383 Area under the curve which overall higher scores than KNN and Decision Tree Models.

Graphical user interface, text, application

Description automatically generated

Figure 6 Overall model results

# Conclusion

In Conclusion, the Random Forest model with hyperparameter with hyperparameters 1 min\_samples\_leaf, 2 min\_samples\_split, None max\_leaf\_nodes, 0.0 min\_weight\_fraction\_leaf, 'entropy' criterion, None max\_features, 121 max\_depth, 'random' splitter applied on oversampled labels and features scaled by using MinMaxScalar gives the best prediction for suicide.

# References

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# Appendix A

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**Coventry** GitHub Repository URL: <https://github.coventry.ac.uk/iftikhars/9789180-SI-s1>

The Demonstration video is present in the Coventry university github and is available online at: <https://github.coventry.ac.uk/iftikhars/9789180-SI-s1>

The dataset used in this project is available on at: <https://www.kaggle.com/dornani/widandsuicide?select=suicidedataextrafestures.csv>

The source code is present in the [Appendix B](#_Appendix_B).

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# Appendix B

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## Downloading required libraries

# pip install imbalanced-learn # used to install imbalanced learn

# pip install xgboost # to install xgboost\_model

# Make sure the version of anaconda is the latest

**import** **sklearn** # importing sklearn

**print**(sklearn.\_\_version\_\_) # printing sklearn version

### Importing the relevent libraries

**import** **numpy** **as** **np** # Allows us to work with arrays.

**import** **pandas** **as** **pd** # importing pandas’ library for use. Allows us to import data set and manipulate it.

**import** **seaborn** **as** **sns** # Allows to polt beautiful plots.

**import** **matplotlib.pyplot** **as** **plt** # Allows working with plots.

**from** **mpl\_toolkits** **import** mplot3d # plotting 3d plots

**from** **sklearn.compose** **import** ColumnTransformer # helps with encoding.

**from** **sklearn.preprocessing** **import** OneHotEncoder # Does onehotencode.

**from** **sklearn.preprocessing** **import** LabelEncoder # Does 1 and 0 encoding.

**from** **sklearn.model\_selection** **import** train\_test\_split # Splits dataset into test set and traning set.

**from** **sklearn.preprocessing** **import** StandardScaler, MinMaxScaler, RobustScaler, Normalizer # Perform the feature scaling.

**from** **sklearn.metrics** **import** confusion\_matrix, ConfusionMatrixDisplay, multilabel\_confusion\_matrix # creates a

# confusion matrix # creates a confusion matrix

**from** **sklearn.metrics** **import** accuracy\_score # Returns accury score of a model.

**from** **collections** **import** Counter # Allows the counting the items in an iterable list.

**from** **sklearn.linear\_model** **import** LogisticRegression # Performs logistic regression.

**from** **sklearn.neighbors** **import** KNeighborsClassifier # applies K Neariesst Neighobour.

**from** **sklearn.neural\_network** **import** MLPClassifier # applies Multilayer Perceptrons neural network

**from** **sklearn.impute** **import** KNNImputer # imputes missing values using KNN.

**from** **sklearn.svm** **import** SVC # applies svm

**from** **sklearn.naive\_bayes** **import** GaussianNB # applies naive\_bayes gaussianNB.

**from** **sklearn.tree** **import** DecisionTreeClassifier # applies decision tree classification model.

**from** **sklearn.ensemble** **import** RandomForestClassifier # applies random forest classification.

**from** **xgboost** **import** XGBClassifier # applies xgboost classification. gradiant decision trees.

**from** **sklearn.decomposition** **import** PCA # applies PCA

**from** **sklearn.model\_selection** **import** cross\_val\_score # performs cross validation. Helps in model selection.

**from** **sklearn.model\_selection** **import** GridSearchCV # helps select the best hyper parameters

**from** **imblearn.over\_sampling** **import** RandomOverSampler # Uses over sampling techniques to Sample the data correctly.

**from** **sklearn.metrics** **import** classification\_report, accuracy\_score, recall\_score, precision\_score, roc\_auc\_score, f1\_score

# Allows the usage of a classification report

**from** **sklearn.metrics** **import** precision\_recall\_fscore\_support # gives precison, recall, f1 score, and support

**from** **sklearn.model\_selection** **import** RandomizedSearchCV # performs randomized search cv

**import** **warnings** # allows to ignore warnings

warnings.filterwarnings("ignore") # ignores warnings

#%matplotlib inline # helps in showing plots on the browser.

### Importing the dataframe

sucidedataframe = pd.read\_csv("suicidedataextrafestures.csv") # opens csv files and assighns them to a variable.

### Checking the data from the dataframe before pre-processing

sucidedataframe.head(**1**) # Taking a look at the dataframe the first elements of the dataset.

sucidedataframe.info() # checking Basic information on the dataframe being procesed.

## 1. Data pre-processing

# Below relevent data is selected that will be used in this project.

sucidedataframe = sucidedataframe[["country", "age" ,"sex", "population", \

"Individuals using the Internet (% of population)", "Labor force, total", \

"Mobile cellular subscriptions (per 100 people)", "GDPpyear","GDPpcapital","Expense (% of GDP)",\

"Physicians (per 1,000 people)","Refugee population by country or territory of origin" ,"suicidesper100k"]]## 1. Data

# pre-processing

sucidedataframe.head(**5**) # out puts data from dataframe

# Below the col names are renamed.

sucidedataframe = sucidedataframe.set\_axis(["Country", "Age", "Gender", "Population", \

"Internet\_Usage\_per\_percent\_Population", "Total\_Labour\_force", "Cellular\_subscriptions\_per\_100\_people", \

"GDPpyear","GDPpcapital","Expense\_percent\_of\_GDP)",\

"Physicians\_per\_1,000\_people)","Refugee\_population\_by\_country\_or\_territory\_of\_origin" ,"Suicidesper100k"],axis=**1**)

sucidedataframe.columns # The columns of the dataframe are viewed.

sucidedataframe.shape # The Entries and the columns of the dataframe are viewed.

### Dealing with null values

sns.heatmap(sucidedataframe.isnull()) # shows null values

sucidedataframe.isnull().sum() # Checking the dataframe for null values.

sucidedataframe.info() # checking basic information on dataframe

#df['Internet\_Usage\_per\_percent\_Population'] = df['DataFrame Column'].fillna(mean(column))

**print**(len(sucidedataframe.Internet\_Usage\_per\_percent\_Population)) # printing lenghth of the column.

**print**(len(sucidedataframe.Refugee\_population\_by\_country\_or\_territory\_of\_origin)) # printing lenghth of the column.

**print**(len(sucidedataframe["Expense\_percent\_of\_GDP)"])) # printing lenghth of the column.

**print**(len(sucidedataframe["Physicians\_per\_1,000\_people)"])) # printing lenghth of the column.

# Function to replace missing values Using KNN

**def** **missng\_values\_filler\_knn**(missingdataframevalue,colname): # function replaces missing values using KNN's. function

# name specified and paramaters given

columntobereplaced = missingdataframevalue.to\_numpy() # The column to be replaced is stored in a variable.

imputer = KNNImputer(n\_neighbors=**10**, weights="uniform") # creating instance of the object.

replaced = imputer.fit\_transform(columntobereplaced) # fitting the model and replaing missing values

**print**(len(replaced)) # printing replaced lenght

dataframe=pd.DataFrame(replaced, columns=colname) # adding replaced values in a dataframe column and giving the column a

# name.

**print**("null values ", dataframe.isnull().sum()) # Checking the dataframe for null values.

**print**(dataframe.head(**5**)) # printing head of new data frame

**return** dataframe # returning the dataframe

# Replacing missing values

sucidedataframe[["Internet\_Usage\_per\_percent\_Population"]] = \

missng\_values\_filler\_knn(sucidedataframe[["Internet\_Usage\_per\_percent\_Population"]], ["Internet\_Usage\_per\_percent\_Population"])

# replacing null values using KNN function

sucidedataframe[["Expense\_percent\_of\_GDP)"]] = \

missng\_values\_filler\_knn(sucidedataframe[["Expense\_percent\_of\_GDP)"]], ["Expense\_percent\_of\_GDP)"])

# replacing null values using KNN function

sucidedataframe[["Refugee\_population\_by\_country\_or\_territory\_of\_origin"]] = \

missng\_values\_filler\_knn(sucidedataframe[["Refugee\_population\_by\_country\_or\_territory\_of\_origin"]],\

["Refugee\_population\_by\_country\_or\_territory\_of\_origin"])

# replacing null values using KNN function

sucidedataframe[["Physicians\_per\_1,000\_people)"]] = \

missng\_values\_filler\_knn(sucidedataframe[["Physicians\_per\_1,000\_people)"]],["Physicians\_per\_1,000\_people)"])

sucidedataframe.isnull().sum() # Checking the dataframe for null values.

sucidedataframe = sucidedataframe.dropna() # droping all rows with at least one null values.

# sucidedataframe.isnull().sum() # Checking the dataframe for null values.

sucidedataframe.shape # The Entries and the columns of the dataframe are viewed.

sucidedataframe.info() # checking Basic information on the dataframe being procesed.

# Reseting index

sucidedataframe.reset\_index(drop=True, inplace=True) # reseting index.

### Looking at outliers.

**def** **outliers\_check**(fig,columnnametocheck): # function with parameters given.

"""

The outlier\_check fuction plots outliers for the sucidedataframe.

The first parameter fig takes a number as argument which is the number of the figure bening plotted.

The second parameter columnnametocheck takes a column anme from sucidedataframe to plot its outliers.

"""

plt.figure(fig) # number of the figure being plotted.

plt.title("Outliers",fontsize=**18**) # Displays plot title

plt.boxplot(sucidedataframe[[columnnametocheck]]) # Displays description of the plots x and y labels.

plt.xlabel(columnnametocheck) # Displays the x axis for the plot

plt.ylabel(columnnametocheck) # Displays the y axis for the plot.

plt.grid() # adds a gird to the plot

plot\_values\_list = ["Population","Internet\_Usage\_per\_percent\_Population", "Total\_Labour\_force",\

"Cellular\_subscriptions\_per\_100\_people" , "GDPpyear", "GDPpcapital", "Expense\_percent\_of\_GDP)", "Physicians\_per\_1,000\_people)",\

"Refugee\_population\_by\_country\_or\_territory\_of\_origin", "Suicidesper100k"] # a list of column names in

# sucidedataframe to use for plotting.

**for** i **in** range(len(plot\_values\_list)): # looping in a range of the length of plot\_values\_list.

outliers\_check(i+**1**,plot\_values\_list[i]) # Arguemnts given to the function.

**def** **relationageandgender**(fig,columnnametocheck): # function with parameters given.

"""

The relationageandgender plots the relationship between a given column from the sucidedatafame with the

Age and Gender column form the same dataframe.

The first parameter fig takes a number as argument which is the number of the figure bening plotted.

The second parameter columnnametocheck takes a column name from sucidedataframe to check its relationship with the

Age and Gender column form the same dataframe.

"""

**print**("plot in respect to ", columnnametocheck) # printing the name of column to be plotted.

plt.figure(fig) # number of the figure being plotted.

plt.style.use('seaborn-white') # style to use for seaborn.

sns.catplot(x='Gender', y=columnnametocheck, col="Age", col\_wrap=**3**, sharey=True, \

data=sucidedataframe, alpha=**0.5**, palette = 'hot') # plots gender and Age in relationship with columnnametocheck.

plt.xticks(rotation = **90**) # rotates plot to 90 degree

plt.show() # shows plot.

**for** i **in** range(len(plot\_values\_list)): # looping in a range of the length of plot\_values\_list.

relationageandgender(i+**1**,plot\_values\_list[i]) # Arguemnts given to the function.

**def** **relationsucide100kwithage**(fig,columnnametocheck): # function with parameters given.

"""

The relationsucide100kwithage plots the relationship between a given column from the sucidedatafame with the

Suicidesper100k, Gender and Age column form the same dataframe.

The first parameter fig takes a number as argument which is the number of the figure bening plotted.

The second parameter columnnametocheck takes a column name from sucidedataframe to check its relationship with the

Suicidesper100k, Gender and Age column form the same dataframe.

"""

plt.figure(fig) # number of the figure being plotted.

My\_plot\_object = sns.FacetGrid(sucidedataframe , row = 'Gender',col = 'Age',margin\_titles=True)

My\_plot\_object.map(plt.scatter,"Suicidesper100k",columnnametocheck,edgecolor = 'w') # plots "Suicidesper100k" column in

# relation to columnnametocheck from sucidedataframe.

plt.show() # shows plot.

**for** i **in** range(len(plot\_values\_list)-**1**): # looping in a range of the length of plot\_values\_list.

relationsucide100kwithage(i+**1**,plot\_values\_list[i]) # Arguemnts given to the function.

# Function to perform OneHotEncoding

**def** **encodingoh**(required\_column,dropped\_column,column\_rename): # function to perform the one hot encoding with parameters given.

"""

encodingoh fuction perfoms OneHotEncoding on a given dataset column.

The first parameter required\_column is the column to be OneHotEncoded.

The second parameter dropped\_column checks if the is a column to be dropped when OneHotEncoding.

for example the arguemnt None drops no columns.

the argement "first" drops the fist column when OneHotEncoding.

The Third parameter column\_rename is the new names of the colums after OneHotEncoding

The encodingoh function returns a one hot encoded dataframe.

"""

oh = OneHotEncoder(drop=dropped\_column,dtype=np.int) # creates the instace of the object.

newdf = required\_column # creates a new data frame from the column to be one hot encoded

newdf = oh.fit\_transform(newdf).toarray() # one hot enocdes the new dataframe as a array

newdf = pd.DataFrame(newdf) # converts the newly created array to a dataframe.

newdf.columns = column\_rename # renames the newly encoded column

**print**(newdf.head(**5**)) # outputs the head of the dataframe.

**return** newdf # returns the one hot encoded data frame

### One Hot Encoding

sucidedataframe.nunique() # outputs unique values in each column in a data frame.

sucidedataframe.duplicated().sum() # gives the sum of duplicate dvalues

**print**(sucidedataframe.pivot\_table(columns=['Gender'], aggfunc='size')) # counts duplicates in the selected dataframe column.

**print**(sucidedataframe.pivot\_table(columns=['Country'], aggfunc='size')) # counts duplicates in the selected dataframe column.

sucidedataframe.head(**1**) # outputs the head of the dataframe

**print**(sucidedataframe.pivot\_table(columns=['Age'], aggfunc='size')) # counts duplicates in the selected dataframe column.

sucidedataframe.index = pd.RangeIndex(len(sucidedataframe.index)) # outputs indext of the data frame

sucidedataframe.head()

### One Hot Encoding

**print**(sucidedataframe.pivot\_table(columns=['Gender'], aggfunc='size')) # prints the unique values of the column.

**print**(sucidedataframe.pivot\_table(columns=['Age'], aggfunc='size')) # prints the unique values of the column.

# one hot enocdes the column using the created function.

age = encodingoh(sucidedataframe[["Age"]], None, ['15-24 years',"25-34 years", "35-54 years", \

"5-14 years", "55-74 years", "75+ years"])

# one hot enocdes the column using the created function.

gender = encodingoh(sucidedataframe[["Gender"]], "first", ["Gender"])

sucidedataframe = sucidedataframe.drop('Age', **1**) # column is dropped

sucidedataframe = sucidedataframe.drop('Gender', **1**) # column is dropped

sucidedataframe.head(**5**) # dataframe head is printed.

sucidedataframe = pd.concat([ gender,sucidedataframe],axis=**1**) # column is concatanated to dataframe

sucidedataframe.head() # fisrt elements of the dataframe are outptted

sucidedataframe = pd.concat([age,sucidedataframe],axis=**1**) # column is concatanated to dataframe

sucidedataframe # fisrt elements of the dataframe are outptted

**print**(sucidedataframe.pivot\_table(columns=['Gender'], aggfunc='size')) # prints the unique values of the column.

**print**(sucidedataframe.pivot\_table(columns=['15-24 years'], aggfunc='size')) # counts duplicates in the selected

# dataframe column.

**print**(sucidedataframe.pivot\_table(columns=["25-34 years"], aggfunc='size')) # counts duplicates in the selected

# dataframe column.

**print**(sucidedataframe.pivot\_table(columns=["35-54 years"], aggfunc='size')) # counts duplicates in the

# selected dataframe column.

**print**(sucidedataframe.pivot\_table(columns=["5-14 years"], aggfunc='size')) # counts duplicates in the

# selected dataframe column.

**print**(sucidedataframe.pivot\_table(columns=["55-74 years"], aggfunc='size')) # counts duplicates in the

# selected dataframe column.

**print**(sucidedataframe.pivot\_table(columns=["75+ years"], aggfunc='size')) # counts duplicates in the

# selected dataframe column.

sucidedataframe.head() # the first elements of the data frame are outputted

sucidedataframe.describe().round() # Shows the count, mean, std, min, 25%, 50%, 75% and

# max of a datframe.

# Checking and selecting higly correlated features

plt.figure(figsize = (**15**,**10**)) # sets the size of the matrix

correlation\_matrix = sucidedataframe.corr().round(**2**) # creates the correlation matrix

sns.heatmap(data = correlation\_matrix, annot = True) # shows correlation matrix

Features\_after\_corelation\_matrix = sucidedataframe[[ "Gender", "5-14 years", "15-24 years", "75+ years"]] # higher correlated

# features are selected

Features\_after\_corelation\_matrix.head() # first elements of the dataframe are outputted.

# count duplicates function learned from: https://datatofish.com/count-duplicates-pandas/

sucidedataframe.pivot\_table(columns=['Country'], aggfunc='size') # counts duplicates in the selected dataframe column.

each\_country = np.unique(sucidedataframe[["Country"]].values) # unique country rows are selected.

each\_country # array is outputted

Country = encodingoh(sucidedataframe[["Country"]], None, each\_country) # each country is one hot encoded at a time.2

sucidedataframe = pd.concat([Country,sucidedataframe],axis=**1**) # each new country is concatanated to original data frame.

sucidedataframe.head() # first elements of the data frame are out putted

Features\_after\_corelation\_matrix = pd.concat([Country,Features\_after\_corelation\_matrix],axis=**1**) # each new country is

# concatanated to highly correlate data frame.

Features\_after\_corelation\_matrix.head() # first elements of the data frame are out putted

**print**(sucidedataframe.columns) # columns of the data frame are printed

sucidedataframe = sucidedataframe.drop('Country', **1**) # country column is dropped.

**print**(sucidedataframe.columns) # columns of the data frame are printed

# Making lables

sucidedataframe.describe().round() # Shows the count, mean, std, min, 25%, 50%, 75% and

# max of a datframe.

# Selecting the values for the labels

**print**("max : ", **178** ) # prints the given input.

**print**("high : ", round(**178** / **2**)) # prints the given input.

**print**("medium :", round(**89** / **2**)) # prints the given input.

**print**("low : ", round(**44** / **2**)) # prints the given input.

**print**("min : ", round(**22** / **2**)) # prints the given input.

# Coverting the values to catagories

sucidedataframe.loc[(sucidedataframe["Suicidesper100k"] < **11**), "Suicidesper100k"] = **1** # Encoding values below 11 as 1.

sucidedataframe.loc[(sucidedataframe["Suicidesper100k"] >= **11**) & (sucidedataframe["Suicidesper100k"] < **22**),\

"Suicidesper100k"] = **2**

# Encoding values aboveor equal to 11 as and below 22 to 2.

sucidedataframe.loc[(sucidedataframe["Suicidesper100k"] >= **22**) & (sucidedataframe["Suicidesper100k"] < **44**),\

"Suicidesper100k"] = **3**

# Encoding values equal to and above 22 and below 44 to 3.

sucidedataframe.loc[(sucidedataframe["Suicidesper100k"] >= **44**) & (sucidedataframe["Suicidesper100k"] < **89**),\

"Suicidesper100k"] = **4**

# Encoding values above or equal to 44 as and below 89 to 4.

sucidedataframe.loc[(sucidedataframe["Suicidesper100k"] >= **89**) & (sucidedataframe["Suicidesper100k"] <= **178**), \

"Suicidesper100k"] = **5**

# Encoding values above or equal to 89 as and below 178 to 4.

sucidedataframe.info() # checking Basic information on the dataframe being procesed.

# Label Encoding

le = LabelEncoder() # creating the instance of the object.

sucidedataframe.Suicidesper100k = le.fit\_transform(sucidedataframe.Suicidesper100k) # label encoing the require dcolumn.

sucidedataframe.info() # checking Basic information on the dataframe being procesed.

**print**(sucidedataframe.pivot\_table(columns=['Suicidesper100k'], aggfunc='size')) # counts duplicates in the selected

# dataframe column.

**9264** + **2850** + **2177** + **678** + **141** # calculation

sucidedataframe.head() # outputting dataframe head.

one = str(round(**100** \* (**9264**/**15110**),**2**)) + "%" # percentage of the value is checked from label column.

two = str(round(**100** \* (**2850**/**15110**),**2**)) + "%" # percentage of the value is checked from label column.

three = str(round(**100** \* (**2177**/**15110**),**2**)) + "%" # percentage of the value is checked from label column.

four = str(round(**100** \* (**678**/**15110**),**2**)) + "%" # percentage of the value is checked from label column.

five = str(round(**100** \* (**141**/**15110**),**2**)) + "%" # percentage of the value is checked from label column.

**print**("1 is represented ", one, "**\n**2 is represented ", two, "**\n**3 is represented ", three, "**\n**4 is represented ", four, "**\n**5 is represented ", five)

# percentage of the value is printed of label column.

plt.bar([**1**,**2**,**3**,**4**,**5**],[**9262**, **2850**, **2177**, **678**, **141**]) # bar chart is outputted to show the difference in values.

sucidedataframe.head() # dataframe head is outputted.

sucidedataframe.info() # checking Basic information on the dataframe being procesed.

### selecting X and Y values

sucidedataframe.head(**1**) # the fisrt elements of the data frame are outputted

Features\_after\_corelation\_matrix.head(**1**) # the fisrt elements of the data frame are outputted

X = sucidedataframe.iloc[:, :-**1**].values # selecting the values for the X variable.

X2 = Features\_after\_corelation\_matrix.iloc[:, :].values # selecting the

# values for the X2 variable.

y = sucidedataframe.iloc[:, -**1**].values # selecting the values for the Y variable. # done using .to\_numpy and not

# .iloc as .to\_numpy creates a horizontal bar while .iloc creates a

# horizontal bar which will not alighn with the x values.

**print**("X ", X, "**\n**", "X2 " , X2 , "**\n**", "y ", y) # priting arrays

# Function to check principal Components

**def** **pcafuntion**(X,pcomponents ,pcolumns, y\_value, y\_var, plot\_labels): # A function to perfrom PCA with paramenters given.

"""

The pcafunction gives the principal components of a given datafame with respect to the selected label.

It also plots a 2d and 3d PCA plot if the number of pca are 2 or 3 respectively.

The first parameters X is the columns from a dataframe as a array to be converted to principal components.

The second parameter pcomponents is the name of the principal componets that are to be added as a list.

For example ['principal component 1','principal component 2'].

The third parameter y\_value is the column from the dataframe to be used as the y variable.

For example df[["y\_var"]]

The fourth parameter y\_var is the name of the y column for the dataframe.

The fifth parameter plot\_labels is the legends for the plot.

The pcafunction function returns the given dataframes required principal comonents concanated with the

y label as a dataframe.

"""

# Normalizing data before applying pca

sc = StandardScaler() # creating an instance of the object.

X = sc.fit\_transform(X) # selecting vaues to perfom transformation on

pca = PCA(n\_components=pcomponents) # selecting number of principal components

principalComponents = pca.fit\_transform(X) # # selecting values to perfom transformation on

principalDf = pd.DataFrame(data = principalComponents # creating a new dataframe with principal components.

, columns =pcolumns)

finalDf = pd.concat([principalDf, y\_value], axis = **1**) # concnating principal componenets with Class.

**print**(finalDf) # looking at the out put from pca.

**print**("**\n**",pca.explained\_variance\_ratio\_)# shows how much information is reatined from the pca

missing = **0** # setting variable to 0.

**for** i **in** range(len(pca.explained\_variance\_ratio\_)): # for looping in length of the array pca.explained\_variance\_ratio\_

missing = missing + pca.explained\_variance\_ratio\_[i] # adding pca.explained\_variance\_ratio\_[i]

# varables values to missing variable

**print**("Total values : ", missing, "%") # total data left

missing = **1** - missing # subtracting missing variables value from 1.

**print**("missing values :", missing, "%") # total data lost

**if** pcomponents == **2**: # checks the number of principal components.

plot = sns.relplot(

x='principal component 1', # selecting first princal component.

y='principal component 2', # selecting second princal component.

hue=y\_var, # sets hue to the y variable.

data=finalDf, # selects where to get data from.

facet\_kws={'legend\_out': False} # helps in selecting a custom legend.

) # plots a scatter plot of principal components.

plt.title('Dataset with pca') # Title of the plot

# check axes and find which is have legend

leg = plot.axes.flat[**0**].get\_legend()

new\_title =y\_var # Legend title.

leg.set\_title(new\_title) # setting title to legend.

leg.get\_frame().set\_alpha(**255**) # setting transparency level for legend box

labels = plot\_labels # label list for legend

**for** t, l **in** zip(plot.\_legend.texts, labels): # looping through a touple.

t.set\_text(l) # adding label to list

**elif** pcomponents == **3**: # checks the number of principal components.

fig = plt.figure(figsize=(**15**,**10**)) # setting plot size

ax = plt.axes(projection='3d') # specifying that it is a 3d plot.

plt.title('Dataset with pca', fontsize=**20**) # adding a title to the plot

# Data for three-dimensional scattered points

xdata = finalDf['principal component 1'] # selecting first princal component.

ydata = finalDf['principal component 2'] # selecting second princal component.

zdata = finalDf['principal component 3'] # selecting third princal component.

ax.scatter3D(xdata, ydata, zdata, c=y\_value) # plotting princhpla components

ax.set\_xlabel("First Principal Component",fontsize=**15**) # setting label for first principal componenet.

ax.set\_ylabel("Second Principal Component",fontsize=**15**) # setting label for second principal componenet.

ax.set\_zlabel("Third Principal Component",fontsize=**15**) # setting label for third principal componenet.

plt.show() # making plot visible.

**return** finalDf # returning finalDf

# Principal component analysis

## Using continues variables

X\_pca = sucidedataframe.iloc[:, **55**:].values

pcafuntion(X\_pca,**2** ,['principal component 1','principal component 2'], sucidedataframe[["Suicidesper100k"]], \

"Suicidesper100k", [**1**,**2**,**3**,**4**,**5**])

pcafuntion(X\_pca,**3** ,['principal component 1','principal component 2', 'principal component 3'], \

sucidedataframe[["Suicidesper100k"]], "Suicidesper100k", [**1**,**2**,**3**,**4**,**5**])

pcom = "principal component "

plist = ['principal component 1','principal component 2', 'principal component 3']

**for** i **in** range(**4**,**10**):

plist.append(pcom + str(i))

**print**("Number of Components ", i)

pcafuntion(X\_pca,i ,plist, sucidedataframe[["Suicidesper100k"]], "Suicidesper100k", [**1**,**2**,**3**,**4**,**5**])

**print**("**\n\n**")

## Over-sampling

**print**('Original dataset shape %s' % Counter(y)) # original data set rows counted

ros = RandomOverSampler(random\_state=**42**) # instance of object created.

X\_over, y\_over = ros.fit\_resample(X, y) # oversampling model fitting

**print**('Resampled dataset shape %s' % Counter(y\_over)) # oversampled data set rows counted

## Spliting the datasets into a training and test set

## Original x and y values.

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size = **0.2**, random\_state = **1**)

# test\_size = 0.2 # splitting the data into 80 and 20 percent between the training and test set

# to get the best results.

# random\_state = 1 # resetting the random seed

# print the lenghth of both test and train set to see if there equally split.

**print**("The length of X\_train is ",len(X\_train), " and the length of y\_train is ", len(y\_train))

**print**("The length of X\_test is ",len(X\_test), " and the length of y\_test is ", len(y\_test))

## Original x and y values after they have been over Sampled.

X\_train\_over, X\_test\_over, y\_train\_over, y\_test\_over = train\_test\_split(X\_over, y\_over, test\_size = **0.2**, random\_state = **1**)

# test\_size = 0.2 # splitting the data into 80 and 20 percent between the training and test set

# to get the best results.

# random\_state = 1 # resetting the random seed

# print the lenghth of both test and train set to see if there equally split.

**print**("The length of X\_train\_over is ",len(X\_train\_over), " and the length of y\_train\_over is ", len(y\_train\_over))

**print**("The length of X\_test\_over is ",len(X\_test\_over), " and the length of y\_test\_over is ", len(y\_test\_over))

## x2 and y2 values choosend by using the corelation matrix.

X2\_train, X2\_test, y2\_train, y2\_test = train\_test\_split(X2, y, test\_size = **0.2**, random\_state = **1**)

# test\_size = 0.2 # splitting the data into 80 and 20 percent between the training and test set

# to get the best results.

# random\_state = 1 # resetting the random seed

# print the lenghth of both test and train set to see if there equally split.

**print**("The length of X2\_train is ",len(X2\_train), " and the length of y2\_train is ", len(y2\_train))

**print**("The length of X2\_test is ",len(X2\_test), " and the length of y2\_test is ", len(y2\_test))

sucidedataframe.info() # checking Basic information on the dataframe being procesed.

# Different models are evaluated.

# Function to evaluate different models

**def** **Classifier\_function**(model, X\_train, y\_train,X\_test,y\_test, title): # function takes the name of the

"""

The Classifier\_function Checks, predicted/actual results , checks testing and traning scores,

Checks Actual values classified correctly and wrongly Checks accuracy, precision, recall, f1

scores and area under the curve.

It plots a confusion matix with accuracy, precision, recall, f1 scores given.

The first parameter is model the model to evaluate.

The secound parameter X\_train is the variable contaning training datas features.

The third parameter y\_train is the variable contaning training datas label.

The fourth parameter X\_test is the variable contaning testing datas features.

The fifth parameter y\_test is the variable contaning testing datas label.

The sixth parameter is the string which will be used as the title for the confusion matrix.

The Classifier\_function function returns the train\_accuracy,test\_accuracy , precision, recall,

f1\_score and Area\_under\_the\_curve of a given model.

"""

# model used, the x and y traning and testing sets.

model.fit(X\_train, y\_train) # Building the k-nearest neighbors classification model.

y\_test\_p = model.predict(X\_test) # Predicted results.

**print**(" results**\n**pred-Actual") # printing predicted and real values.

**print**(np.concatenate((y\_test\_p.reshape(len(y\_test\_p),**1**),y\_test.reshape(len(y\_test),**1**)),**1**)) # Predicted results and

# real results in a np array.

train\_accuracy = round(model.score(X\_train,y\_train),**2**) \* **100** # Getting traing accuracy multipling it by 100 after

# rounding it by 2 to get a score between 0 to 100

test\_accuracy = round(model.score(X\_test,y\_test),**2**) \* **100** # Getting testing accuracy multipling it by 100 after

# rounding it by 2 to get a score between 0 to 100

**print**("Model train accuracy: ", train\_accuracy, "%") # printing the model accurcy.

**print**("Model test accuracy: ", test\_accuracy, "%") # printing the model accurcy.

**print**("**\n\n**") # printing a new line.

# getting Accuracy or recall or precision or specificity

y\_test\_pred = model.predict(X\_test) # predicted results

cReport = classification\_report(y\_test,y\_test\_pred) # creating a Classification report

**print**(cReport) # creating a Classification report

cm = confusion\_matrix(y\_test, y\_test\_p) # creating the confusion matrix

cm2 = multilabel\_confusion\_matrix(y\_test, y\_test\_pred) # creating a mutable confusion matrix

precision, recall, f1\_score, support = precision\_recall\_fscore\_support(y\_test, y\_test\_pred) # getting the precision,

# recall and f1score for later use.

accuracy = round(np.trace(cm) / float(np.sum(cm)), **2**) \* **100** # getting aaccuracy and multipling it by 100 after

# rounding it by 2 to get a score between 0 to 100.

precision = round(np.mean(precision),**2**) \* **100** # multipling precision variables mean by 100 after rounding it by

# 2 to get a score between 0 to 100.

recall = round(np.mean(recall),**2**) \* **100** # multipling recall variables mean by 100 after rounding it by 2 to

# get a score between 0 to 100.

f1\_score = round(np.mean(f1\_score),**2**) \* **100** # multipling f1\_score variables mean by 100 after rounding

# it by 2 to get a score between 0 to 100.

lable\_list = [] # creating a empty list

**for** i **in** range(len(cm)): # looping in the range of the length of the confusion matrix.

**for** j **in** range(len(cm)): # looping in the range of the length of the confusion matrix.

**if** j == i: # if the value of j is equal to the value of i.

# the below code appends the Actual Values Classified correctly to the variable lable\_list.

lable\_list.append("Actual "+ str(i) +"**\n**" + "calssified as "+ str(j) +"**\n**" + str(cm[i][j]) + "**\n**"+ \

str(round(cm[i][j]/np.sum(cm),**2**)) + " %")

**else**: # otherwise

# the below function appends the actual values classified wrongly to the variable lable list.

lable\_list.append("Actual "+ str(i) +"**\n**" + "calssified as "+ str(j) + "**\n**" + str(cm[i][j]) + "**\n**"+ \

str(round(cm[i][j]/np.sum(cm),**2**)) + " %")

lable\_list = np.asarray(lable\_list).reshape(len(cm),len(cm)) # resahping the label list as a numpy array to be

# used in plotting the confusion matrix

# the variable function will be will be used to display the results of the evaluation to the confusion matrix.

total\_score = ("Accuracy: " + str(accuracy) +" %" + "**\n**Precison: " + str(precision) +" %" + "**\n**Recall: " +\

str(recall) +" %" + "**\n**F1 score: " + str(f1\_score) +" %")

# Below is the code used to plot the confusion matrix.

plt.figure(figsize = (**12**,**9**)) # sets the size of the matrix

disp = sns.heatmap(cm, annot=lable\_list, fmt='', cmap='Blues') # displays the results of the actual values

# classified wrongly and correctly.

disp.plot() # displaying data in plot

plt.title(title, fontsize=**25**) # adding a title to plot

plt.ylabel('True label', fontsize=**20**) # adding a y axis to the plot.

plt.xlabel('Predicted label' +"**\n\n**Scores**\n**" +total\_score, fontsize=**20**) # adding a x axis to the plot

plt.show() # showing the plot

y\_pred\_proba = model.predict\_proba(X\_test)

Area\_under\_the\_curve = roc\_auc\_score(y\_test, y\_pred\_proba, multi\_class="ovr")

**print**("Area under the curve: ", Area\_under\_the\_curve)

result\_list = train\_accuracy,test\_accuracy , precision, recall, f1\_score,Area\_under\_the\_curve # returning the results

**return** result\_list # returns the results from the model.

# Feature Scaling and testing function

**def** **featurescaling**(Scaler, X\_train, X\_test, y\_train, y\_test, Modelandprams ,Modelname):

"""

The featurescaling fundtion feature scales given features and then Checks, predicted/actual results , checks testing and traning scores,

Checks Actual values classified correctly and wrongly Checks accuracy, precision, recall, f1

scores and area under the curve.

It plots a confusion matix with accuracy, precision, recall, f1 scores given.

The first parameter is typpe of scaling technique to use.

The secound parameter X\_train is the variable contaning training datas features.

The third parameter y\_train is the variable contaning training datas label.

The fourth parameter X\_test is the variable contaning testing datas features.

The fifth parameter y\_test is the variable contaning testing datas label.

The sixth parameter is parameter is model the model to evaluate.

The seventh parameter is the string which will be used as the title for the confusion matrix.

The featurescaling function returns the train\_accuracy,test\_accuracy , precision, recall,

f1\_score and Area\_under\_the\_curve of a given model after feature scaling.

"""

sucidedataframe.info() # checking Basic information on the dataframe being procesed.

sc = Scaler # creating an instance of the object.

**print**("Before scaling:**\n**X\_test ", X\_test,"**\n\n**X\_train ", X\_train) # printing the sets before feature scaling.

X\_train[:, **55**:] = sc.fit\_transform(X\_train[:, **55**:]) # Scaling x\_train

X\_test[:,**55**:] = sc.transform(X\_test[:, **55**:]) # Scaling y\_train

**print**("After scaling:**\n**X\_test ", X\_test,"**\n\n**X\_train ", X\_train) # printing the sets after feature scaling.

**print**("**\n**The result of the model")

train\_accuracy,test\_accuracy , precision, recall, f1\_score, Area\_under\_the\_curve =Classifier\_function(Modelandprams ,\

X\_train, y\_train,X\_test, y\_test, Modelname)

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

**return** train\_accuracy,test\_accuracy , precision, recall, f1\_score, Area\_under\_the\_curve

# Evaluating different models to choose which one to use

## k-fold cross-validation

**def** **crossvalscore**(model, X, y, cv\_val): # function to perform cross validation with model X, y and cv\_val as parameters

"""

The crossvalscore function prints the avarage coross validation accuracy of a model and its standard deveation.

The first parameter model is the type of model to perform the cross validation on.

The second parameter X is the features.

The third parameter y is the labels.

the foruth parameter cv\_val is the number of times to cross validate the given model.

The crossvalscore function returns the mean accuracy of the model.

"""

score = cross\_val\_score(estimator = model, X = X, y = y, cv = cv\_val) # performs different tests to get best accurecy.

**print**("Accuracy: {:.2f} %".format(score.mean()\***100**)) # accuracy printed.

**print**("Standard Deviation: {:.2f} %".format(score.std()\***100**)) # standard deveation printed (std -avarage or std+ avarage )

**return** round(score.mean(),**2**)\***100**, round(score.std(),**2**)\***100**

model\_name = ["Logistc Regression", "KNN", "Naive Bayes", "Neural Networks", "Decision Tree", "Random Forest"]

Accuracy\_list = [] # making empty list

std\_list = [] # making empty list

# Logistic

crossvalscore(LogisticRegression(), X, y, **10**) # Performs cross validation.

Accuracy, std = crossvalscore(LogisticRegression(), X\_over, y\_over, **10**) # Performs cross validation.

Accuracy\_list.append(Accuracy) # appending to list

std\_list.append(std) # appending to list

crossvalscore(LogisticRegression(), X2, y, **10**) # Performs cross validation.

# KNN

crossvalscore(KNeighborsClassifier(), X, y, **10**) # Performs cross validation.

Accuracy, std = crossvalscore(KNeighborsClassifier(), X\_over, y\_over, **10**) # Performs cross validation.

Accuracy\_list.append(Accuracy) # appending to list

std\_list.append(std) # appending to list

crossvalscore(KNeighborsClassifier(), X2, y, **10**) # Performs cross validation.

# Naive bayes

crossvalscore(GaussianNB(), X, y, **10**) # Performs cross validation.

Accuracy, std = crossvalscore(GaussianNB(), X\_over, y\_over, **10**) # Performs cross validation.

Accuracy\_list.append(Accuracy) # appending to list

std\_list.append(std) # appending to list

crossvalscore(GaussianNB(), X2, y, **10**) # Performs cross validation.

# Neural Network

crossvalscore(MLPClassifier(), X, y, **10**) # Performs cross validation.

Accuracy, std = crossvalscore(MLPClassifier(), X\_over, y\_over, **10**) # Performs cross validation.

Accuracy\_list.append(Accuracy) # appending to list

std\_list.append(std) # appending to list

crossvalscore(MLPClassifier(), X2, y, **10**) # Performs cross validation.

# Decision Tree

crossvalscore(DecisionTreeClassifier(), X, y, **10**) # Performs cross validation.

Accuracy, std = crossvalscore(DecisionTreeClassifier(), X\_over, y\_over, **10**) # Performs cross validation.

Accuracy\_list.append(Accuracy) # appending to list

std\_list.append(std) # appending to list

crossvalscore(DecisionTreeClassifier(), X2, y, **10**) # Performs cross validation.

# Random Forest

crossvalscore(RandomForestClassifier(), X, y, **10**) # Performs cross validation.

Accuracy, std = crossvalscore(RandomForestClassifier(), X\_over, y\_over, **10**) # Performs cross validation.

Accuracy\_list.append(Accuracy) # appending to list

std\_list.append(std) # appending to list

crossvalscore(RandomForestClassifier(), X2, y, **10**) # Performs cross validation.

Evaluation2 = pd.DataFrame({

'Model':model\_name,

'Crossvaladation Accuracy':Accuracy\_list,

'Standard deveation':std\_list,

}) # using lists to make a dataframe

Evaluation2

Evaluation2.sort\_values(by='Crossvaladation Accuracy', ascending=False) # viewing dataframe information by recall in decending order.

Evaluation2.sort\_values(by='Standard deveation', ascending=True) # viewing dataframe information by recall in decending order.

**def** **plot\_bar\_graph**(list\_for\_plot, list\_for\_plot2,Accuracy\_type, colour): # funstion with given parameters.

"""

The function plot\_bar\_graph plots a bar graph.

The first parameter list\_for\_plot is the x axis.

The second parameter list\_for\_plot2 is the y axis.

The third parameter Accuracy\_type takes a string.

for example "F1 score"

The fourth parameter colour is the color for the bar plot.

"""

plt.figure() # plots figure

plt.title("Model Evaluation",fontsize=**18**) # Displays plot title

plt.bar(list\_for\_plot, list\_for\_plot2, color = colour) # Displays description of the plots x and y labels.

plt.xlabel("Models") # Displays the x axis for the plot

plt.ylabel(Accuracy\_type) # Displays the y axis for the plot.

plt.grid() # adds a gird to the plot

plot\_bar\_graph(model\_name, Accuracy\_list , "accuracy", "red") # functions argents given. plots output using given data.

plot\_bar\_graph(model\_name, std\_list , "standard deveation", "blue") # functions argents given. plots output using given data.

# KNN Model

## k-fold cross-validation Graph

**def** **subplot**(list\_for\_plot, ave\_scores, hyper\_pram\_to\_use\_name): # A function with parameters given.

"""

The function subplot plots a linear plot and shows the best results using two lists

the fist one acting as a label to the second list and the second list being scores.

The first parameter list\_for\_plot is the X label.

The second parameter ave\_scores is the y label.

The thrid paramater hyper\_pram\_to\_use\_name is the the titile for the plot.

"""

**print**(hyper\_pram\_to\_use\_name + " ", list\_for\_plot,"**\n**Average " + hyper\_pram\_to\_use\_name +\

" scores", ave\_scores) # printing the average score of the model

**for** i **in** range(len(ave\_scores)): # looping to the legth of list

**if** ave\_scores[i] == max(ave\_scores): # if the first value is equal to the second value

**print**("The hyperparameter",list\_for\_plot[i], "gives the best result :", ave\_scores[i]) # print output.

**print**("**\n\n**") # print new line

plt.figure() # plot a figure

plt.title("Best " + hyper\_pram\_to\_use\_name + " Selection",fontsize=**18**) # Displays plot title

plt.plot(list\_for\_plot, ave\_scores) # Displays description of the plots x and y labels.

plt.xlabel(hyper\_pram\_to\_use\_name +" values") # Displays the x axis for the plot

plt.ylabel("Average CV model accuracy") # Displays the y axis for the plot

plt.legend([hyper\_pram\_to\_use\_name], loc="lower right") # adds a legend to the plot.

plt.grid() # adds a gird to the plot

**def** **K\_NN\_plot\_Values**(X,y): # A function with parameters given.

"""

The K\_NN\_plot\_Values performs cross valadation on the KNN models all hyperparametes, prints

the best hyperparameters that give the best reults and plots the results

The first parameter X takes the features.

The first parameter y takes the lables.

"""

ave\_scores = [] # Creating a empty list

k\_list = k\_list = list(range(**1**,**50**)) # Setting the values for the list variable.

**for** single\_val **in** k\_list: # looping through each value in the k\_list variable

model = KNeighborsClassifier(n\_neighbors = single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**,scoring="accuracy") # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(k\_list, ave\_scores, "n\_neighbors") # using the function to plot x and y values.

ave\_scores = [] # Creating a empty list

weight\_list = ["uniform", "distance"] # weights list uniform and distance

**for** single\_val **in** weight\_list: # looping through each value in the list variable

model = KNeighborsClassifier(weights = single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**,scoring="accuracy") # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(weight\_list, ave\_scores, "weights") # using the function to plot x and y values

ave\_scores = [] # Creating a empty list

metric\_list = ['minkowski','euclidean','manhattan'] # a list of KNN metrics

**for** single\_val **in** metric\_list: # looping through each value in the list variable

model = KNeighborsClassifier(metric = single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**,scoring="accuracy") # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(metric\_list, ave\_scores, "metric") # using the function to plot x and y values

ave\_scores = [] # Creating a empty list

algorithm\_list = ['auto', 'ball\_tree', 'kd\_tree', 'brute']

**for** single\_val **in** algorithm\_list: # looping through each value in the list variable

model = KNeighborsClassifier(algorithm = single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**,scoring="accuracy") # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(algorithm\_list, ave\_scores, "algorithm") # using the function to plot x and y values

ave\_scores = [] # Creating a empty list

leaf\_size\_list = list(range(**1**,**30**)) # a list of KNN metrics

**for** single\_val **in** leaf\_size\_list: # looping through each value in the list variable

model = KNeighborsClassifier(algorithm = 'ball\_tree', leaf\_size = single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**,scoring="accuracy") # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(leaf\_size\_list, ave\_scores, "Algorithm Ball tree leaf\_size") # using the function to plot x and y values

ave\_scores = [] # Creating a empty list

leaf\_size\_list = list(range(**1**,**30**)) # a list of KNN metrics

**for** single\_val **in** leaf\_size\_list: # looping through each value in the list variable

model = KNeighborsClassifier(algorithm = 'kd\_tree', leaf\_size = single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**,scoring="accuracy") # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(leaf\_size\_list, ave\_scores, "Algorithm Kd leaf\_size") # using the function to plot x and y values

# X and y un\_edited

## Plotting the KNN's with a average Cross-val score

K\_NN\_plot\_Values(X,y) # PLots KNN Cross Val score

# Over Sampled X and y values

## Plotting the KNN's with a average Cross-val score

K\_NN\_plot\_Values(X\_over,y\_over) # PLots KNN Cross Val score

# X and y obtained by using Corelation matrix

## Plotting the KNN's with a average Cross-val score

K\_NN\_plot\_Values(X2,y) # PLots KNN Cross Val score

# X and y un\_edited

# Without any model Tuning

crossvalscore(KNeighborsClassifier(), X, y, **10**) # Performs cross validation.

# Using Cross Validation hyperparameter selection

crossvalscore(KNeighborsClassifier(weights = 'uniform', n\_neighbors = **30**), X, y, **10**) # Performs cross validation.

# Over Sampled X and y values

# Without any model Tuning

crossvalscore(KNeighborsClassifier(), X\_over, y\_over, **10**) # Performs cross validation.

# Using Cross Validation hyperparameter selection

crossvalscore(KNeighborsClassifier(weights = 'distance', n\_neighbors = **1**), X\_over, y\_over, **10**) # Performs cross validation.

# X and y obtained by using Corelation matrix

# Without any model Tuning

crossvalscore(KNeighborsClassifier(), X, y, **10**) # Performs cross validation.

# Using Cross Validation hyperparameter selection

leaf\_size\_list = [**1**,**24**,**25**,**26**,**27**,**28**,**29**] # a list of leaf sizes.

**for** lsz **in** leaf\_size\_list: # looping in a list.

**print**("When Leaf Size = ", lsz) # printing output

crossvalscore(KNeighborsClassifier(weights = 'uniform', n\_neighbors = **17**,algorithm = 'ball\_tree', \

leaf\_size = lsz), X, y, **10**) # Performs cross validation.

**print**("**\n**") # printing a new line.

leaf\_size\_list = [**1**,**24**,**25**,**26**,**27**,**28**,**29**] # a list of leaf\_size

**for** lsz **in** leaf\_size\_list: # looping through a list

**print**("When Leaf Size = ", lsz) # printing output

crossvalscore(KNeighborsClassifier(weights = 'distance', n\_neighbors = **17**,algorithm = 'ball\_tree', \

leaf\_size = lsz), X, y, **10**) # Performs cross validation.

**print**("**\n**") # printing new line

leaf\_size\_list = [**24**,**25**,**26**,**27**,**28**,**29**] # a list of leaf\_size

**for** lsz **in** leaf\_size\_list: # looping through a list

**print**("When Leaf Size = ", lsz) # printing output

crossvalscore(KNeighborsClassifier(weights = 'uniform', n\_neighbors = **17**,algorithm = 'ball\_tree', \

leaf\_size = lsz), X, y, **10**) # Performs cross validation.

**print**("**\n**") # printing new line

leaf\_size\_list = [**24**,**25**,**26**,**27**,**28**,**29**]

**for** lsz **in** leaf\_size\_list:

**print**("When Leaf Size = ", lsz)

crossvalscore(KNeighborsClassifier(weights = 'distance', n\_neighbors = **17**,algorithm = 'ball\_tree', \

leaf\_size = lsz), X, y, **10**) # Performs cross validation.

**print**("**\n**")

# Random Search plot

**def** **Random\_search\_plot**(sorted\_list1, sorted\_list2, sorted\_uniform, sorted\_distance, single\_val):

"""

The function Random\_search\_plot is used to make a plot for the random search out put for KNN.

The first parameter sorted\_list1 is a list used for the first x axis.

The secound parameter sorted\_list2 is a list used for the secound x axis.

The third parameter sorted\_uniform is a list used for the first y axis.

The fourth parameter sorted\_distance is a list used for the second y axis.

The fifth parameter single\_val is used as the title of the plot

"""

plt.figure(dpi=**100**, figsize=(**14**, **7**)) # setting the plot size

plt.title("Random Search Hyper parameter Comparison with " + single\_val + " metric",\

fontsize=**25**, color="blue") # setting the plot title.

plt.plot(sorted\_list1,sorted\_uniform , "--",marker = "o", label="weights uniform", color="red") # setting the

# uniform variables

# values to the plot on the y axis and K\_list on the x axis.

plt.plot(sorted\_list2,sorted\_distance , ":",marker = "\*", label="weights distant", color="blue") # setting the distant

# variables values to the plot on the y axis and K\_list

# on the x axis.

plt.xlabel("Number of nearest neighbours", fontsize=**20**) # Setting the x label.

plt.ylabel("Avarage CV Score", fontsize=**20**) # setting the y label.

plt.legend(loc='upper left') # setting the legend.

plt.grid() # setting a grid

# sub function to preform Random Search

**def** **rand\_search\_fun**(typeofmodelandprams, dict\_prams,crossval, X, y): # Function takes in the model type,

# number of crossvalidation sand X and y values as hyperparameters.

"""

The function rand\_search\_fun performs random search on a model. It prints the best results and

the hyperparametrs used to obtain those results and then it plots those results.

The first parameter typeofmodelandprams is the type of model used on which random search is performed on.

The secound parameter dict\_prams is a dictinory of hyperparameters to be used in the random search.

The third parameter crossval is the number of cross validations to be performed.

The fourth parameter X is the features.

The fifth parameter y is the labels.

The function rand\_search\_fun returns the results of the random search.

"""

model = typeofmodelandprams # creating an instance of the object.

parameters = [dict\_prams] # hyper parameters for the random search

rand\_search = RandomizedSearchCV(

model,

#estimator = model, # model

#param\_distributions = parameters, # hyper paramaters

parameters,

scoring = 'accuracy', # score measurement

cv = crossval, # number of cross validations

n\_jobs = -**1**, # selecting all possible paramaters to go through to get the best model possible

return\_train\_score=False, # train score is false as it can be computationaly

# expensive. without storing the traning score the grd search is fater

n\_iter=**10**, # setting the number of iterations

random\_state=**5**)

rand\_search.fit(X, y) # applying the search on our model.

#print(pd.DataFrame(rand\_search.cv\_results\_)[["mean\_test\_score","params"]])

**print**(pd.DataFrame(rand\_search.cv\_results\_)) # to print the whole result

best\_accuracy = rand\_search.best\_score\_ # the best accuracy

best\_parameters = rand\_search.best\_params\_ # the best paramaters that gave the best accurecy

**print**("Best Accuracy: {:.2f} %".format(best\_accuracy\***100**)) # printing best accuracy

**print**("Best Parameters:", best\_parameters) # printing the best parameters

**print**(parameters) # prininting the parameters

**return** rand\_search # return random search value.

# Performs full Random Search on KNN Model

**def** **KNN\_full\_rand\_search**(X, y): # performs randomized search

"""

The function KNN\_full\_rand\_search performs random search on KNN model. It prints the best results and

the hyperparametrs used to obtain those results and then it plots those results.

The first parameter X is the features.

The secound parameter y is the labels.

"""

metric\_list = ['minkowski','euclidean','manhattan']

k\_list = list(range(**1**,**31**)) # list from 1 - 30 (will be used as KNN's)

**for** single\_val **in** metric\_list:

weight\_list = ["uniform"] # weights list uniform and distance

para\_rand = dict(n\_neighbors=k\_list,weights=weight\_list, metric=[single\_val]) # adding the above lists in a dictinorr.

rand\_search = rand\_search\_fun(KNeighborsClassifier(), para\_rand, **5**, X, y) # Using the grid search gunction with

# arguments given

uniform = [] # creating a empty list

k\_list1 = [] # creating a empty list

**for** i **in** range(len(rand\_search.cv\_results\_["mean\_test\_score"])): # looping through the times the length of

# the mean\_test\_score

uniform.append(rand\_search.cv\_results\_["mean\_test\_score"][i]) # appending the uniform values ot the

# uniform variable.

k\_list1.append(rand\_search.cv\_results\_["param\_n\_neighbors"][i]) # appedning the KNN's to the K\_list1.

sorted\_uniform = [] # creating a empty list

sorted\_list1 = k\_list1.copy() # creating a copy of the K\_list1 variables values.

sorted\_list1.sort() # sorting the KNNs

**for** i **in** range(len(sorted\_list1)): # Looping through the lenght of the sorted\_list1 variable.

**for** j **in** range(len(k\_list1)): # Looping through the lenght of the K\_list1 variable.

**if** sorted\_list1[i] == k\_list1[j]: # checking that if the values of sorted\_list1[i] is equal to k\_list1[j]

sorted\_uniform.append(uniform[j]) # appeding the unifrom[j] values to the sorted\_uniform list.

weight\_list = ["distance"] # weights list distance

para\_rand = dict(n\_neighbors=k\_list,weights=weight\_list,metric=[single\_val]) # adding the above lists in a dictinory.

**print**("**\n**unsorted kNN ",k\_list1) # checking out put of the given variables values

**print**("sorted KNN ", sorted\_list1) # checking out put of the given variables values

**print**("unsorted Uniform ", uniform) # checking out put of the given variables values

**print**("sorted uniform ", sorted\_uniform, "**\n**") # checking out put of the given variables values

rand\_search = rand\_search\_fun(KNeighborsClassifier(), para\_rand, **5**, X, y) # Using the grid search gunction with

# arguments given

distance = [] # creating a empty list

k\_list2 = [] # creating a empty list

**for** i **in** range(len(rand\_search.cv\_results\_["mean\_test\_score"])): # looping through the times the length of

# the mean\_test\_score

distance.append(rand\_search.cv\_results\_["mean\_test\_score"][i]) # appending the distance values ot the

# distance variable.

k\_list2.append(rand\_search.cv\_results\_["param\_n\_neighbors"][i]) # appedning the KNN's to the K\_list2.

sorted\_distance = [] # creating a empty list

sorted\_list2 = k\_list2.copy() # creating a copy of the K\_list2 variables values.

sorted\_list2.sort() # sorting the KNNs

**for** i **in** range(len(sorted\_list2)): # Looping through the lenght of the sorted\_list2 variable.

**for** j **in** range(len(k\_list2)): # Looping through the lenght of the K\_list2 variable.

**if** sorted\_list2[i] == k\_list2[j]: # checking that if the values of sorted\_list2[i] equal k\_list2[j]

sorted\_distance.append(distance[j]) # appeding the unifrom[j] values to the sorted\_uniform list.

**print**("**\n**unsorted KNN ", k\_list2) # checking out put of the given variables values

**print**("sorted KNN ", sorted\_list2) # checking out put of the given variables values

**print**("unsorted distance ", distance) # checking out put of the given variables values

**print**("sorted distance ", sorted\_distance,"**\n**") # checking out put of the given variables values

Random\_search\_plot(sorted\_list1, sorted\_list2, sorted\_uniform, sorted\_distance, single\_val)

# X and y un\_edited

## Random search

KNN\_full\_rand\_search(X, y) # performs random search.

# Over Sampled X and y values

## Random search

KNN\_full\_rand\_search(X\_over, y\_over) # performs random search.

# X and y obtained by using Corelation matrix

## Random search

KNN\_full\_rand\_search(X2, y) # performs random search.

# Grid Search plot

**def** **grid\_search\_plot**(distance, uniform, k\_list, single\_val):

"""

The function grid\_search\_plot is used to make a plot for the grid search out put for KNN.

The first parameter distance is a list used for the second y axis.

The secound parameter uniform is a list used for the first y axis.

The third parameter k\_list is a list used for the first x and second axis.

The fourth parameter single\_val is used as the title of the plot

"""

**print**("distance ", distance) # printing the values distace variable.

**print**("uniform ", uniform) # printing the values uniform variable.

**print**("**\n\n\n**")

plt.figure(dpi=**100**, figsize=(**14**, **7**)) # setting the plot size

plt.title("Grid Search Hyper parameter Comparison with " + single\_val + " metric",\

fontsize=**25**, color="blue") # setting the plot title.

plt.plot(k\_list,uniform , "--", marker = "o", label="weights uniform", color="red") # setting the uniform

# variables values to the plot on the y axis and K\_list on the x axis.

plt.plot(k\_list,distance ,":", marker = "\*", label="weights distant", color="blue") # setting the distant

# variables values to the plot on the y axis and K\_list on the x axis.

plt.xlabel("Number of nearest neighbours",fontsize=**20**) # Setting the x label.

plt.ylabel("Avarage CV Score",fontsize=**20**) # setting the y label.

plt.legend(loc='lower left') # setting the legend.

plt.grid() # setting a grid

# Sub function to preform Grid Search

**def** **Grid\_search\_fun**(typeofmodelandprams, dict\_prams, crossval, X, y): # Function takes in the model type,

# number of crossvalidation sand X and y values as hyperparameters.

"""

The function Grid\_search\_fun performs grid search on a model. It prints the best results and

the hyperparametrs used to obtain those results and then it plots those results.

The first parameter typeofmodelandprams is the type of model used on which random search is performed on.

The secound parameter dict\_prams is a dictinory of hyperparameters to be used in the random search.

The third parameter crossval is the number of cross validations to be performed.

The fourth parameter X is the features.

The fifth parameter y is the labels.

The function Grid\_search\_fun returns the results of the gird search.

"""

model = typeofmodelandprams # creating an instance of the object.

parameters = [dict\_prams] # hyper parameters for the grid search

grid\_search = GridSearchCV(estimator = model, # model

param\_grid = parameters, # hyper paramaters

scoring = 'accuracy', # score measurement

cv = crossval, # number of cross validations

n\_jobs = -**1**, return\_train\_score=False) # selecting all possible paramaters to go

# through to get the best model possible # train score is false as it can be computationaly expensive.

# without storing the traning score the grd search is fater

grid\_search.fit(X, y) # applying the search on our model.

#print(pd.DataFrame(grid\_search.cv\_results\_)[["mean\_test\_score","params"]])

**print**(pd.DataFrame(grid\_search.cv\_results\_)) # to print the whole result

best\_accuracy = grid\_search.best\_score\_ # the best accuracy

best\_parameters = grid\_search.best\_params\_ # the best paramaters that gave the best accurecy

**print**("Best Accuracy: {:.2f} %".format(best\_accuracy\***100**)) # printing best accuracy

**print**("Best Parameters:", best\_parameters) # printing the best parameters

**return** grid\_search # returns grid search value

# Performs full grid search for KNN model

**def** **KNN\_full\_grid\_search**(X, y): # Performs grid search.

"""

The function KNN\_full\_grid\_search performs grid search on KNN model. It prints the best results and

the hyperparametrs used to obtain those results and then it plots those results.

The first parameter X is the features.

The secound parameter y is the labels.

"""

metric\_list = ['minkowski','euclidean']

**for** single\_val **in** metric\_list:

k\_list = list(range(**1**,**31**)) # list from 1 - 31 (will be used as KNN's)

weight\_list = ["uniform", "distance"] # weights list uniform and distance

para\_grid = dict(n\_neighbors=k\_list,weights=weight\_list,metric=[single\_val])

# adding the above lists in a dictinary.

grid\_search = Grid\_search\_fun(KNeighborsClassifier(n\_neighbors=k\_list), para\_grid, **5**, X, y) # Using the grid

# search function with arguments given

grid\_search.cv\_results\_["mean\_test\_score"] # looking at mean test score

uniform = [] # a empty list is created

**for** i **in** range(len(grid\_search.cv\_results\_["mean\_test\_score"])): # getting all even number

# indexes using a for loop.

**if** grid\_search.cv\_results\_["param\_weights"][i] == "uniform":

uniform.append(grid\_search.cv\_results\_["mean\_test\_score"][i]) # appending the unifrom values to the

# varibale unifrom.

distance = [] # a empty list is created

**for** i **in** range(len(grid\_search.cv\_results\_["mean\_test\_score"])): # getting all odd number indexes

# using a for loop.

**if** grid\_search.cv\_results\_["param\_weights"][i] == "distance":

distance.append(grid\_search.cv\_results\_["mean\_test\_score"][i]) # appending the distance values to the

# varibale distance.

grid\_search\_plot(distance, uniform, k\_list, single\_val)

# X and y un\_edited

## Grid Search

KNN\_full\_grid\_search(X, y) # performs grid search.

# Over Sampled X and y values

## Grid Search

KNN\_full\_grid\_search(X\_over, y\_over) # performs grid search.

# X and y obtained by using Corelation matrix

## Grid Search

KNN\_full\_grid\_search(X2, y) # performs grid search.

# Model Evaluation using hyperparameters obtained using.

# Cross Valadation

# Random Search

# Grid Search

# X and y un\_edited

## Checking predicted/actual results

## Checking testing and traning scores

## Checking Actual values classified correctly and wrongly.

## Checking accuracy, precision, recall and f1 scores

**for** neighbour **in** [**1**, **11**, **29**]: # looping from a list.

**print**("When neighbour = ", neighbour) # printing output

Classifier\_function(KNeighborsClassifier(weights = 'uniform', n\_neighbors = neighbour), X\_train,\

y\_train,X\_test, y\_test, "KNN Model")

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Results after feature scaling

# StandardScaler

**for** neighbour **in** [**1**, **11**, **29**]: # looping from a list.

**print**("When neighbour = ", neighbour) # printing output

featurescaling(StandardScaler(), X\_train, X\_test, y\_train, y\_test,\

KNeighborsClassifier(weights = 'uniform', n\_neighbors = neighbour) ,"KNN Model")

# performs standard scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# MinMaxScaler

**for** neighbour **in** [**1**, **11**, **29**]: # looping from a list.

**print**("When neighbour = ", neighbour) # printing output

featurescaling(MinMaxScaler(), X\_train, X\_test, y\_train, y\_test,\

KNeighborsClassifier(weights = 'uniform', n\_neighbors = neighbour) ,"KNN Model")

# performs Minmax scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# RobustScaler

**for** neighbour **in** [**1**, **11**, **29**]: # looping from a list.

**print**("When neighbour = ", neighbour) # printing output

featurescaling(RobustScaler(), X\_train, X\_test, y\_train, y\_test,\

KNeighborsClassifier(weights = 'uniform', n\_neighbors = neighbour) ,"KNN Model")

# performs robust scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Normalizer

**for** neighbour **in** [**1**, **11**, **29**]: # looping from a list.

**print**("When neighbour = ", neighbour) # printing output

featurescaling(Normalizer(), X\_train, X\_test, y\_train, y\_test,\

KNeighborsClassifier(weights = 'uniform', n\_neighbors = neighbour) ,"KNN Model")

# Performs normalization scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Over Sampled X and y values

## Checking predicted/actual results

## Checking testing and traning scores

## Checking Actual values classified correctly and wrongly.

## Checking accuracy, precision, recall and f1 scores

**for** neighbour **in** [**1**, **3**, **15**]: # looping from a list.

**print**("When neighbour = ", neighbour) # printing output

Classifier\_function(KNeighborsClassifier(n\_neighbors = neighbour, weights ='distance'), X\_train\_over,\

y\_train\_over, X\_test\_over, y\_test\_over, "KNN Model")

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Feature scaling

# StandardScaler

**for** neighbour **in** [**1**, **3**, **15**]: # looping from a list.

**print**("When neighbour = ", neighbour) # printing output

featurescaling(StandardScaler(), X\_train\_over, X\_test\_over, y\_train\_over, y\_test\_over,\

KNeighborsClassifier(n\_neighbors = neighbour, weights ='distance') ,"KNN Model")

# performs standard scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# MinMaxScaler

**for** neighbour **in** [**1**, **3**, **15**]: # looping from a list.

**print**("When neighbour = ", neighbour) # printing output

featurescaling(MinMaxScaler(), X\_train\_over, X\_test\_over, y\_train\_over, y\_test\_over,\

KNeighborsClassifier(n\_neighbors = neighbour, weights ='distance') ,"KNN Model")

# performs Minmax scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# RobustScaler

**for** neighbour **in** [**1**, **3**, **15**]: # looping from a list.

**print**("When neighbour = ", neighbour) # printing output

featurescaling(RobustScaler(), X\_train\_over, X\_test\_over, y\_train\_over, y\_test\_over,\

KNeighborsClassifier(n\_neighbors = neighbour, weights ='distance') ,"KNN Model")

# performs robust scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Normalizer

**for** neighbour **in** [**1**, **3**, **15**]: # looping from a list.

**print**("When neighbour = ", neighbour) # printing output

featurescaling(Normalizer(), X\_train\_over, X\_test\_over, y\_train\_over, y\_test\_over,\

KNeighborsClassifier(n\_neighbors = neighbour, weights ='distance') ,"KNN Model")

# Performs normalization scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# X and y obtained by using Corelation matrix

## Checking predicted/actual results

## Checking testing and traning scores

## Checking Actual values classified correctly and wrongly.

## Checking accuracy, precision, recall and f1 scores

**for** neighbour **in** [**17**,**19**]: # looping through a list

**print**("When neighbour = ", neighbour) # printing output

Classifier\_function(KNeighborsClassifier(n\_neighbors = neighbour, weights = "uniform"), X2\_train, y2\_train,\

X2\_test, y2\_test, "KNN Model")

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

leaf\_size\_list = [**24**,**25**,**26**,**27**,**28**,**29**] # creating a list

**for** lsz **in** leaf\_size\_list: # looping through a list

**print**("When Leaf Size = ", lsz) # printing output

crossvalscore(KNeighborsClassifier(weights = 'uniform', n\_neighbors = **19**,algorithm = 'ball\_tree', \

leaf\_size = lsz), X, y, **10**) # Performs cross validation.

**print**("**\n**") # printing new line

leaf\_size\_list = [**24**,**25**,**26**,**27**,**28**,**29**] # creating a list

**for** lsz **in** leaf\_size\_list: # looping through a list

**print**("When Leaf Size = ", lsz) # printing output

Classifier\_function(KNeighborsClassifier(n\_neighbors = **19**, weights = "uniform", algorithm = 'ball\_tree', \

leaf\_size = lsz), X2\_train, y2\_train,X2\_test, y2\_test, "KNN Model")

**print**("**\n**") # printing new line

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Results

# Original results without hyperparameter Improvement

Classifier\_function(KNeighborsClassifier(), X\_train, y\_train,X\_test, y\_test, "KNN Model")

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Best Score and model

# Over Sampled X and y values

# MinMaxScaler

# results with hyparameters improved

featurescaling(MinMaxScaler(), X\_train\_over, X\_test\_over, y\_train\_over, y\_test\_over,\

KNeighborsClassifier(n\_neighbors = **3**, weights ='distance') ,"KNN Model")

# performs Minmax scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

featurescaling(MinMaxScaler(), X\_train\_over, X\_test\_over, y\_train\_over, y\_test\_over,\

KNeighborsClassifier(n\_neighbors = **15**, weights ='distance') ,"KNN Model")

# performs Minmax scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Checking Best Results with different Random\_states

sucidedataframe.info() # checking Basic information on the dataframe being procesed.

# Un edited full evalution

crossvalscore(KNeighborsClassifier(), X\_over, y\_over, **10**) # Performs cross validation.

# Improved model full Evaluation with feature scaling

# With 15 neighbours

crossvalscore(KNeighborsClassifier(n\_neighbors = **15**, weights ='distance'), X\_over, y\_over, **10**) # Performs cross validation.

# With 3 neighbours

crossvalscore(KNeighborsClassifier(n\_neighbors = **3**, weights ='distance'), X\_over, y\_over, **10**) # Performs cross validation.

# With 1 neighbour

crossvalscore(KNeighborsClassifier(n\_neighbors = **1**, weights ='distance'), X\_over, y\_over, **10**) # Performs cross validation.

# Random forest Model

## k-fold cross-validation Graph

**def** **subplot**(list\_for\_plot, ave\_scores, hyper\_pram\_to\_use\_name): # A function with parameters given.

"""

The function subplot plots a linear plot and shows the best results using two lists

the fist one acting as a label to the second list and the second list being scores.

The first parameter list\_for\_plot is the X label.

The second parameter ave\_scores is the y label.

The thrid paramater hyper\_pram\_to\_use\_name is the the titile for the plot.

"""

**print**(hyper\_pram\_to\_use\_name + " ", list\_for\_plot,"**\n**Average " + hyper\_pram\_to\_use\_name +\

" scores", ave\_scores) # printing the average score of the model

**for** i **in** range(len(ave\_scores)): # looping to the legth of list

**if** ave\_scores[i] == max(ave\_scores): # if the first value is equal to the second value

**print**("The hyperparameter",list\_for\_plot[i], "gives the best result :", ave\_scores[i]) # print output.

**print**("**\n\n**") # print new line

plt.figure() # plot a figure

plt.title("Best " + hyper\_pram\_to\_use\_name + " Selection",fontsize=**18**) # Displays plot title

plt.plot(list\_for\_plot, ave\_scores) # Displays description of the plots x and y labels.

plt.xlabel(hyper\_pram\_to\_use\_name +" values") # Displays the x axis for the plot

plt.ylabel("Average CV model accuracy") # Displays the y axis for the plot

plt.legend([hyper\_pram\_to\_use\_name], loc="lower right") # adds a legend to the plot.

plt.grid() # adds a gird to the plot

**def** **RandomForest\_plot\_Values**(X,y, n\_estimators\_list, max\_depth\_list, min\_samples\_leaf\_list, min\_samples\_split\_list):

# Values required for plotting

"""

The RandomForest\_plot\_Values performs cross valadation on the Random Forest models provided hyperparametes, prints

the best hyperparameters that give the best reults and plots the results.

The first parameter X takes the features.

The first parameter y takes the lables.

The third parameter n\_estimators\_list is a list of n\_estimators.

The fourth parameter max\_depth\_list is a list of max\_depth.

The fifth parameter min\_samples\_leaf\_list is a list of min\_samples\_leaf.

The sixth parameter min\_samples\_split\_list is a list of min\_samples\_split.

"""

ave\_scores = [] # Creating a empty list

**for** single\_val **in** n\_estimators\_list: # looping through each value in the list

model = RandomForestClassifier(n\_estimators=single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**) # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(n\_estimators\_list, ave\_scores, "n\_estimators") # using the function to plot x and y values.

ave\_scores = [] # Creating a empty list

**for** single\_val **in** max\_depth\_list: # looping through each value in the list

model = RandomForestClassifier(max\_depth=single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**) # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(max\_depth\_list, ave\_scores, "max\_depth") # using the function to plot x and y values.

ave\_scores = [] # Creating a empty list

**for** single\_val **in** min\_samples\_leaf\_list: # looping through each value in the list

model = RandomForestClassifier(min\_samples\_leaf=single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**) # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(min\_samples\_leaf\_list, ave\_scores, "min\_samples\_leaf") # using the function to plot x and y values.

ave\_scores = [] # Creating a empty list

**for** single\_val **in** min\_samples\_split\_list: # looping through each value in the list

model = RandomForestClassifier(min\_samples\_split=single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**) # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(min\_samples\_split\_list, ave\_scores, "min\_samples\_split") # using the function to plot x and y values.

## Plotting the Random Forest with a average Cross-val score

n\_estimators\_list = [**10**,**50**,**100**,**200**, **300**, **500**] # Setting the values for the list.

max\_depth\_list = [None, **4**,**5**,**6**,**7**,**8** ,**80**, **90**, **100**, **200**,**500**] # Setting the values for the list.

min\_samples\_leaf\_list = list(range(**1**,**30**)) # Setting the values for the list.

min\_samples\_split\_list = list(range(**2**,**30**)) # Setting the values for the list.

# X and y un\_edited

RandomForest\_plot\_Values(X,y, n\_estimators\_list, max\_depth\_list, min\_samples\_leaf\_list, min\_samples\_split\_list)

# PLots KNN Cross Val score

# Over Sampled X and y values

## Plotting the KNN's with a average Cross-val score

RandomForest\_plot\_Values(X\_over,y\_over, n\_estimators\_list, max\_depth\_list, min\_samples\_leaf\_list, min\_samples\_split\_list)

# PLots Cross Val score

# X and y obtained by using Corelation matrix

## Plotting the Random Forest with a average Cross-val score

RandomForest\_plot\_Values(X2,y, n\_estimators\_list, max\_depth\_list, min\_samples\_leaf\_list, min\_samples\_split\_list)

# PLots Cross Val score

**def** **n\_estimation**(X,y): # a function with parameters given

"""

The n\_estimation performs cross valadation on the Random Forest models n\_estimators parameter prints

the best hyperparameters that give the best reults and plots the results

The first parameter X takes the features.

The first parameter y takes the lables.

"""

n\_estimators\_list = [**10**,**15**,**25**,**30**,**45**,**50**,**60**,**75**,**90**,**95**,**100**,**105**,**110**,**125**,**130**,**145**,**150**,**160**,**175**,**190**,**200**,**210**,\

**225**,**230**,**250**,**275**,**300**] # a list of n\_estimators.

ave\_scores = [] # Creating a empty list

**for** single\_val **in** n\_estimators\_list: # looping through each value in the list

model = RandomForestClassifier(n\_estimators=single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**) # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(n\_estimators\_list, ave\_scores, "n\_estimators") # using the function to plot x and y values.

# X and y un\_edited

# N estimation improvement

n\_estimation(X,y) # PLots Cross Val score

# Over Sampled X and y values

# N estimation improvement

n\_estimation(X\_over,y\_over) # PLots Cross Val score

# X and y obtained by using Corelation matrix

# N estimation improvement

n\_estimation(X2,y) # PLots Cross Val score

**def** **max\_depth\_estimation**(X,y):

"""

The max\_depth\_estimation( performs cross valadation on the Random Forest models max\_depth parameter prints

the best hyperparameters that give the best reults and plots the results

The first parameter X takes the features.

The first parameter y takes the lables.

"""

max\_depth\_list = [None, **1**, **5**,**10**, **15**,**20** ,**25**, **30**,**40**,**45**,**50**, **60**,**70**,**75**, **80**, **85**,**90**,**95**,**100**] # a list of max\_depth values.

ave\_scores = [] # Creating a empty list

**for** single\_val **in** max\_depth\_list: # looping through each value in the list

model = RandomForestClassifier(max\_depth=single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**) # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(max\_depth\_list, ave\_scores, "max\_depth") # using the function to plot x and y values.

# X and y un\_edited

# Max depth improvement

max\_depth\_estimation(X,y)

# PLots Cross Val score

# Over Sampled X and y values

# Max depth improvement

max\_depth\_estimation(X\_over,y\_over) # PLots Cross Val score

# X and y obtained by using Corelation matrix

# Max depth improvement

max\_depth\_estimation(X2,y) # PLots Cross Val score

# n\_estimators = [10, 75, 150, 225]

# max\_depth = [10, 50 ,100, 75 , 90]

# min\_samples\_leaf = [1,9, 10]

# min\_samples\_split = [2,16, 20]

# X and y un\_edited

# Without any model Tuning

crossvalscore(RandomForestClassifier(), X, y, **10**) # Performs cross validation.

# Using Cross Validation hyperparameter selection

n\_list = [**110**, **190**, **300**] # a list of n\_estimators

**for** i **in** n\_list: # looping through a list

**print**("Result when n\_estimators = ", i) # printing output

crossvalscore(RandomForestClassifier(n\_estimators = i, max\_depth = **10**, min\_samples\_leaf = **18**, min\_samples\_split =**19**\

), X, y, **10**) # Performs cross validation.

**print**("**\n**") # priting a new line.

# Over Sampled X and y values

# Without any model Tuning

crossvalscore(RandomForestClassifier(), X\_over, y\_over, **10**)

# Performs cross validation.

# Using Cross Validation hyperparameter selection

n\_list = [**90**, **95**, **100**] # a list of n\_estimators

md\_list = [None, **50**, **75**] # a list of max\_depth

**for** n **in** n\_list: # looping through a list

**for** md **in** md\_list: # looping through a list

**print**("Result when n\_estimators = ", n) # printing output

**print**("Result when max depth = ", md) # printing output

crossvalscore(RandomForestClassifier(n\_estimators = n, max\_depth = md, min\_samples\_leaf = **1**, min\_samples\_split =**2**\

), X\_over, y\_over, **10**) # Performs cross validation.

**print**("**\n**") # printing new line

# X and y obtained by using Corelation matrix

# Without any model Tuning

crossvalscore(RandomForestClassifier(), X2, y, **10**)

# Performs cross validation.

# Using Cross Validation hyperparameter selection

n\_list = [**110**, **230**, **250**] # a list of n\_estimators

mss\_list = [**11**, **18**] # a list of n\_estimators

**for** i **in** n\_list: # looping through a list

**for** j **in** mss\_list: # looping through a list

**print**("Result when n\_estimators = ", i) # printing output

**print**("Result when min\_sample\_split = ", j) # printing output

crossvalscore(RandomForestClassifier(n\_estimators =i, max\_depth = **25**, min\_samples\_leaf = **12**, \

min\_samples\_split =j ), X2, y, **10**)

# Performs cross validation.

**print**("**\n**") # printing new line

# Full random search on random forest

**def** **randomsearchrandomforest**(X,y,n\_estimators\_list,max\_depth\_list,min\_samples\_leaf\_list,min\_samples\_split\_list):

"""

The function randomsearchrandomforest performs random search on a model. It prints the best results and

the hyperparametrs used to obtain those results and then it plots those results.

The first parameter X is the feature.

The secound parameter y is the labels

The third parameter n\_estimators\_list is the n\_estimators.

The fourth parameter max\_depth\_list is the max\_depth.

The fifth parameter min\_samples\_leaf\_list is the min\_samples\_leaf.

The sixth parameter min\_samples\_split\_list is the min\_samples\_split.

"""

bootstrap\_list = [True, False] # a lsit with values specified.

max\_features\_list = ['auto', 'sqrt', 'log2'] # Setting the values for the list.

criterion\_list = ['gini', 'entropy'] # Setting the values for the list.

**for** i **in** range(len(criterion\_list)):

**for** j **in** range(len(max\_features\_list)):

list1 = [] # creating a empty list

list2 = [] # creating a empty list

para\_rand = dict(n\_estimators = n\_estimators\_list, max\_depth = max\_depth\_list, min\_samples\_leaf = \

min\_samples\_leaf\_list,min\_samples\_split = min\_samples\_split\_list,\

max\_features = [max\_features\_list[j]], criterion = [criterion\_list[i]],\

bootstrap = bootstrap\_list) # adding the above

# lists in a dictinary.

rand\_search = rand\_search\_fun(RandomForestClassifier(), para\_rand, **5**, X, y) # Using the grid search gunction with

## Random search # Using the grid search gunction with

**for** m **in** range(len(rand\_search.cv\_results\_["mean\_test\_score"])): # looping through the times the length of

# the mean\_test\_score

list1.append(rand\_search.cv\_results\_["mean\_test\_score"][m]) # appending the values to list

list2.append(rand\_search.cv\_results\_["param\_bootstrap"][m]) # appedning the values to the list2.

sorted\_list1= []

sorted\_list2 = list2.copy() # creating a copy of the list2 variables values.

sorted\_list2.sort() # sorting the list2

**for** k **in** range(len(sorted\_list2)): # Looping through the lenght of the sorted\_list2 variable.

**for** l **in** range(len(list2)): # Looping through the lenght of the list2 variable.

**if** sorted\_list2[k] == list2[l]: # checking that if the values of sorted\_list2[i]

# is equal to list2[j]

sorted\_list1.append(list1[l]) # appeding the list1[j] values to the sorted\_list1 list.

plt.figure(dpi=**100**, figsize=(**14**, **7**)) # setting the plot size

plt.title("Random Search Hyper parameter Comparison with "+ criterion\_list[i] +" criterion", \

fontsize=**25**, color="blue") # setting the plot title.

plt.plot(sorted\_list2,sorted\_list1 , "--", marker = "o", label="max features " + max\_features\_list[j],\

color="red") # setting the best

# variables values to the plot on the y axis and max depth on the x axis.

plt.xlabel('bootstrap',fontsize=**20**) # Setting the x label.

plt.ylabel("Avarage CV Score",fontsize=**20**) # setting the y label.

plt.legend(loc='upper left') # setting the legend.

plt.grid() # setting a grid

# X and y un\_edited

## Random search

n\_estimators\_list = [**110**] # a lsit with values specified.

max\_depth\_list = [**10**] # a lsit with values specified.

min\_samples\_leaf\_list = [**18**] # a lsit with values specified.

min\_samples\_split\_list = [**19**] # a lsit with values specified.

randomsearchrandomforest(X,y,n\_estimators\_list,max\_depth\_list,min\_samples\_leaf\_list,min\_samples\_split\_list) # function with arguments given

# Over Sampled X and y values

## Random search

n\_estimators\_list = [**100**] # a lsit with values specified.

max\_depth\_list = [**50**] # a lsit with values specified.

min\_samples\_leaf\_list = [**1**] # a lsit with values specified.

min\_samples\_split\_list = [**2**] # a lsit with values specified.

randomsearchrandomforest(X\_over,y\_over,n\_estimators\_list,max\_depth\_list,min\_samples\_leaf\_list,min\_samples\_split\_list) # function with arguments given

# X and y obtained by using Corelation matrix

## Random search

n\_estimators\_list = [**230**] # a lsit with values specified.

max\_depth\_list = [**18**] # a lsit with values specified.

min\_samples\_leaf\_list = [**12**] # a lsit with values specified.

min\_samples\_split\_list = [**18**] # a lsit with values specified.

randomsearchrandomforest(X2,y,n\_estimators\_list,max\_depth\_list,min\_samples\_leaf\_list,min\_samples\_split\_list) # function with arguments given

# Full Grid search on random forest

**def** **randomforestgridsearch**(X, y, n\_estimators\_list, max\_depth\_list, min\_samples\_leaf\_list, min\_samples\_split\_list): # function

# with parameters given

"""

The function randomforestgridsearch performs grid search on a model. It prints the best results and

the hyperparametrs used to obtain those results and then it plots those results.

The first parameter X is the feature.

The secound parameter y is the labels

The third parameter n\_estimators\_list is the n\_estimators.

The fourth parameter max\_depth\_list is the max\_depth.

The fifth parameter min\_samples\_leaf\_list is the min\_samples\_leaf.

The sixth parameter min\_samples\_split\_list is the min\_samples\_split.

"""

bootstrap\_list = [True, False] # a lsit with values specified.

max\_features\_list = ['auto', 'sqrt', 'log2'] # Setting the values for the list.

criterion\_list = ['gini', 'entropy'] # Setting the values for the list.

**for** i **in** range(len(criterion\_list)):

**if** i == **0**:

para\_grid = dict(n\_estimators = n\_estimators\_list, max\_depth = max\_depth\_list, min\_samples\_leaf = \

min\_samples\_leaf\_list,\

min\_samples\_split = min\_samples\_split\_list,max\_features = max\_features\_list, \

criterion = [criterion\_list[i]], bootstrap = bootstrap\_list) # adding the above

# lists in a dictinary.

grid\_search = Grid\_search\_fun(RandomForestClassifier(), para\_grid, **5**, X, y) # Using the grid search function with

**if** i == **1**:

para\_grid = dict(n\_estimators = n\_estimators\_list, max\_depth = max\_depth\_list, min\_samples\_leaf = \

min\_samples\_leaf\_list,min\_samples\_split = min\_samples\_split\_list,\

max\_features = max\_features\_list,criterion = [criterion\_list[i]],\

bootstrap = bootstrap\_list) # adding the above

# lists in a dictinary.

grid\_search2 = Grid\_search\_fun(RandomForestClassifier(), para\_grid, **5**, X, y) # Using the grid search function with

list1 = [] # a empty list is created

**for** i **in** range(len(grid\_search.cv\_results\_["mean\_test\_score"])): # getting all even number

# indexes using a for loop.

**if** grid\_search.cv\_results\_["param\_max\_features"][i] == 'auto':

list1.append(grid\_search.cv\_results\_["mean\_test\_score"][i]) # appending the 32 values to the

# varibale list1.

list2 = [] # a empty list is created

**for** i **in** range(len(grid\_search.cv\_results\_["mean\_test\_score"])): # getting all odd number indexes

# using a for loop.

**if** grid\_search.cv\_results\_["param\_max\_features"][i] == 'sqrt':

list2.append(grid\_search.cv\_results\_["mean\_test\_score"][i]) # appending the 33 values to the

# varibale list2.

list3 = [] # a empty list is created

**for** i **in** range(len(grid\_search.cv\_results\_["mean\_test\_score"])): # getting all odd number indexes

# using a for loop.

**if** grid\_search.cv\_results\_["param\_max\_features"][i] == 'log2':

list3.append(grid\_search.cv\_results\_["mean\_test\_score"][i]) # appending the 34 values to the

# varibale lst3.

plt.figure(dpi=**100**, figsize=(**14**, **7**)) # setting the plot size

plt.title("Grid Search Hyper parameter Comparison with gini criterion", fontsize=**25**, color="blue")

# setting the plot title.

plt.plot(bootstrap\_list,list1 , "--", marker = "o", label="max features list auto", color="red") # setting the best

plt.plot(bootstrap\_list,list2 ,":", marker = "\*", label="max features list sqrt", color="blue") # setting the random

plt.plot(bootstrap\_list,list3 ,":", marker = "d", label="max features list log2", color="orange") # setting the random

# variables values to the plot on the y axis and max depth on the x axis.

plt.xlabel('bootstrap',fontsize=**20**) # Setting the x label.

plt.ylabel("Avarage CV Score",fontsize=**20**) # setting the y label.

plt.legend(loc='upper left') # setting the legend.

plt.grid() # setting a grid

list1 = [] # a empty list is created

**for** i **in** range(len(grid\_search2.cv\_results\_["mean\_test\_score"])): # getting all even number

# indexes using a for loop.

**if** grid\_search2.cv\_results\_["param\_max\_features"][i] == 'auto':

list1.append(grid\_search2.cv\_results\_["mean\_test\_score"][i]) # appending the 32 values to the

# varibale list1.

list2 = [] # a empty list is created

**for** i **in** range(len(grid\_search2.cv\_results\_["mean\_test\_score"])): # getting all odd number indexes

# using a for loop.

**if** grid\_search2.cv\_results\_["param\_max\_features"][i] == 'sqrt':

list2.append(grid\_search2.cv\_results\_["mean\_test\_score"][i]) # appending the 33 values to the

# varibale list2.

list3 = [] # a empty list is created

**for** i **in** range(len(grid\_search2.cv\_results\_["mean\_test\_score"])): # getting all odd number indexes

# using a for loop.

**if** grid\_search2.cv\_results\_["param\_max\_features"][i] == 'log2':

list3.append(grid\_search2.cv\_results\_["mean\_test\_score"][i]) # appending the 34 values to the

# varibale list3.

plt.figure(dpi=**100**, figsize=(**14**, **7**)) # setting the plot size

plt.title("Grid Search Hyper parameter Comparison with 31 min samples split", fontsize=**25**, color="blue")

# setting the plot title.

plt.plot(bootstrap\_list,list1 , "--", marker = "o", label="max features list auto", color="red") # setting the best

plt.plot(bootstrap\_list,list2 ,":", marker = "\*", label="max features list sqrt", color="blue") # setting the random

plt.plot(bootstrap\_list,list3 ,":", marker = "d", label="max features list log2", color="orange") # setting the random

# variables values to the plot on the y axis and max depth on the x axis.

plt.xlabel('bootstrap',fontsize=**20**) # Setting the x label.

plt.ylabel("Avarage CV Score",fontsize=**20**) # setting the y label.

plt.legend(loc='upper left') # setting the legend.

plt.grid() # setting a grid

# X and y un\_edited

## Grid Search

n\_estimators\_list = [**110**] # a lsit with values specified.

max\_depth\_list = [**10**] # a lsit with values specified.

min\_samples\_leaf\_list = [**18**] # a lsit with values specified.

min\_samples\_split\_list = [**19**] # a lsit with values specified.

randomforestgridsearch(X, y, n\_estimators\_list, max\_depth\_list, min\_samples\_leaf\_list, min\_samples\_split\_list) # function

# with arguments given.

# Over Sampled X and y values

## Grid Search

n\_estimators\_list = [**90**] # a lsit with values specified.

max\_depth\_list = [**50**] # a lsit with values specified.

min\_samples\_leaf\_list = [**1**] # a lsit with values specified.

min\_samples\_split\_list = [**2**] # a lsit with values specified.

randomforestgridsearch(X\_over, y\_over, n\_estimators\_list, max\_depth\_list, min\_samples\_leaf\_list, min\_samples\_split\_list) # function

# with arguments given.

# X and y obtained by using Corelation matrix

## Grid Search

n\_estimators\_list = [**230**] # a lsit with values specified.

max\_depth\_list = [**18**] # a lsit with values specified.

min\_samples\_leaf\_list = [**12**] # a lsit with values specified.

min\_samples\_split\_list = [**18**] # a lsit with values specified.

randomforestgridsearch(X, y, n\_estimators\_list, max\_depth\_list, min\_samples\_leaf\_list, min\_samples\_split\_list) # function

# with arguments given.

# X and y un\_edited

## Checking predicted/actual results

## Checking testing and traning scores

## Checking Actual values classified correctly and wrongly.

## Checking accuracy, precision, recall and f1 scores

Classifier\_function(RandomForestClassifier(n\_estimators =**110**,min\_samples\_split = **19**,\

min\_samples\_leaf = **18**, max\_depth = **10**, bootstrap = True, \

max\_features = 'sqrt', criterion = 'entropy' ), X\_train, y\_train,X\_test, y\_test, "Random Forest")

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Results after feature scaling

# StandardScaler

featurescaling(StandardScaler(), X\_train, X\_test, y\_train, y\_test, \

RandomForestClassifier(n\_estimators =**110**,min\_samples\_split = **19**,min\_samples\_leaf = **18**, \

max\_depth = **10**, bootstrap = True, max\_features = 'sqrt', criterion = 'entropy' ),\

"Random Forest")

# performs standard scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# MinMaxScaler

featurescaling(MinMaxScaler(), X\_train, X\_test, y\_train, y\_test, \

RandomForestClassifier(n\_estimators =**110**,min\_samples\_split = **19**,min\_samples\_leaf = **18**, \

max\_depth = **10**, bootstrap = True, max\_features = 'sqrt', criterion = 'entropy' ),\

"Random Forest")

# performs Minmax scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# RobustScaler

featurescaling(RobustScaler(), X\_train, X\_test, y\_train, y\_test, \

RandomForestClassifier(n\_estimators =**110**,min\_samples\_split = **19**,min\_samples\_leaf = **18**, \

max\_depth = **10**, bootstrap = True, max\_features = 'sqrt', criterion = 'entropy' ),\

"Random Forest")

# performs robust scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Normalizer

featurescaling(Normalizer(), X\_train, X\_test, y\_train, y\_test, \

RandomForestClassifier(n\_estimators =**110**,min\_samples\_split = **19**,min\_samples\_leaf = **18**, \

max\_depth = **10**, bootstrap = True, max\_features = 'sqrt', criterion = 'entropy' ),\

"Random Forest")

# Performs normalization scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Over Sampled X and y values

## Checking predicted/actual results

## Checking testing and traning scores

## Checking Actual values classified correctly and wrongly.

## Checking accuracy, precision, recall and f1 scores

Classifier\_function(RandomForestClassifier(n\_estimators =**90**,min\_samples\_split = **2**,\

min\_samples\_leaf = **1**, max\_depth = **50**, bootstrap = False, \

max\_features = 'sqrt', criterion = 'entropy'), X\_train\_over, y\_train\_over,X\_test\_over, \

y\_test\_over, "Random Forest")

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Feature scaling

# StandardScaler

featurescaling(StandardScaler(), X\_train\_over, X\_test\_over, y\_train\_over, y\_test\_over,\

RandomForestClassifier(n\_estimators =**90**,min\_samples\_split = **2**, min\_samples\_leaf = **1**, max\_depth = **50**,\

bootstrap = False, max\_features = 'sqrt', criterion = 'entropy') ,"Random Forest")

# performs standard scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# MinMaxScaler

featurescaling(MinMaxScaler(), X\_train\_over, X\_test\_over, y\_train\_over, y\_test\_over,\

RandomForestClassifier(n\_estimators =**90**,min\_samples\_split = **2**, min\_samples\_leaf = **1**, max\_depth = **50**,\

bootstrap = False, max\_features = 'sqrt', criterion = 'entropy') ,"Random Forest")

# performs Minmax scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# RobustScaler

featurescaling(RobustScaler(), X\_train\_over, X\_test\_over, y\_train\_over, y\_test\_over,\

RandomForestClassifier(n\_estimators =**90**,min\_samples\_split = **2**, min\_samples\_leaf = **1**, max\_depth = **50**,\

bootstrap = False, max\_features = 'sqrt', criterion = 'entropy') ,"Random Forest")

# performs robust scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Normalizer

featurescaling(Normalizer(), X\_train\_over, X\_test\_over, y\_train\_over, y\_test\_over,\

RandomForestClassifier(n\_estimators =**90**,min\_samples\_split = **2**, min\_samples\_leaf = **1**, max\_depth = **50**,\

bootstrap = False, max\_features = 'sqrt', criterion = 'entropy') ,"Random Forest")

# Performs normalization scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# X and y obtained by using Corelation matrix

## Checking predicted/actual results

## Checking testing and traning scores

## Checking Actual values classified correctly and wrongly.

## Checking accuracy, precision, recall and f1 scores

Classifier\_function(RandomForestClassifier(n\_estimators =**230**,min\_samples\_split = **2**,\

min\_samples\_leaf = **12**, max\_depth = **18**, bootstrap = False, \

max\_features = 'sqrt', criterion = 'entropy'), X2\_train, y2\_train,X2\_test, y2\_test, "Random Forest")

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Results

# Original results without hyperparameter Improvement

Classifier\_function(RandomForestClassifier(), X\_train, y\_train,X\_test, y\_test, "Random Forest")

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Best Score and model

# Over Sampled X and y values

# MinMaxScaler

# Results with hyparameters improved

featurescaling(MinMaxScaler(), X\_train\_over, X\_test\_over, y\_train\_over, y\_test\_over,\

RandomForestClassifier(n\_estimators =**90**,min\_samples\_split = **2**, min\_samples\_leaf = **1**, max\_depth = **50**,\

bootstrap = False, max\_features = 'sqrt', criterion = 'entropy') ,"Random Forest")

# performs Minmax scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Un\_edited full model evaluation

crossvalscore(RandomForestClassifier(), X\_over, y\_over, **10**) # Performs cross validation.

# Improved model full Evaluation with feature scaling

crossvalscore(RandomForestClassifier(n\_estimators =**90**,min\_samples\_split = **2**, min\_samples\_leaf = **1**,\

max\_depth = **50**,bootstrap = False, max\_features = 'sqrt', criterion = 'entropy'), X\_over, y\_over, **10**)

# Performs cross validation.

# Decision Tree

**def** **DecisionTree\_plot\_Values**(X,y, max\_depth\_list, min\_samples\_leaf\_list, min\_samples\_split\_list, min\_weight\_fraction\_leaf\_list,\

max\_leaf\_nodes\_list, criterion\_list,max\_features\_list, splitter\_list):

# Values required for plotting

"""

The DecisionTree\_plot\_Values performs cross valadation on the Decision Tree models provided hyperparametes, prints

the best hyperparameters that give the best reults and plots the results.

The first parameter X takes the features.

The first parameter y takes the lables.

The third parameter max\_depth\_list is a list of max\_depth.

The fourth parameter min\_samples\_leaf\_list is a list of min\_samples\_leaf.

The fifth parameter min\_weight\_fraction\_leaf\_list is a min\_weight\_fraction\_leaf.

The sixth parameter max\_leaf\_nodes\_list is a list of max\_leaf\_nodes.

The seventh parameter criterion\_list is a list of criterion.

The eigth parameter max\_features\_list is a max\_features.

The ningth parameter splitter\_list is a list of splitter.

"""

ave\_scores = [] # Creating a empty list

**for** single\_val **in** max\_depth\_list: # looping through each value in the list

model = DecisionTreeClassifier(max\_depth=single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**) # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(max\_depth\_list, ave\_scores, "max\_depth") # using the function to plot x and y values.

ave\_scores = [] # Creating a empty list

**for** single\_val **in** min\_samples\_leaf\_list: # looping through each value in the list

model = DecisionTreeClassifier(min\_samples\_leaf=single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**) # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(min\_samples\_leaf\_list, ave\_scores, "min\_samples\_leaf") # using the function to plot x and y values.

ave\_scores = [] # Creating a empty list

**for** single\_val **in** min\_samples\_split\_list: # looping through each value in the list

model = DecisionTreeClassifier(min\_samples\_split=single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**) # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(min\_samples\_split\_list, ave\_scores, "min\_samples\_split") # using the function to plot x and y values.

ave\_scores = [] # Creating a empty list

**for** single\_val **in** min\_weight\_fraction\_leaf\_list: # looping through each value in the list

model = DecisionTreeClassifier(min\_weight\_fraction\_leaf=single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**) # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(min\_weight\_fraction\_leaf\_list, ave\_scores, "min\_weight\_fraction\_leaf") # using the function to plot x and y values.

ave\_scores = [] # Creating a empty list

**for** single\_val **in** max\_leaf\_nodes\_list: # looping through each value in the list

model = DecisionTreeClassifier(max\_leaf\_nodes=single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**) # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(max\_leaf\_nodes\_list, ave\_scores, "max\_leaf\_nodes") # using the function to plot x and y values.

ave\_scores = [] # Creating a empty list

**for** single\_val **in** criterion\_list: # looping through each value in the list

model = DecisionTreeClassifier(criterion=single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**) # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(criterion\_list, ave\_scores, "criterion") # using the function to plot x and y values.

ave\_scores = [] # Creating a empty list

**for** single\_val **in** max\_features\_list: # looping through each value in the list

model = DecisionTreeClassifier(max\_features=single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**) # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

max\_features\_list[**3**] = "None"

subplot(max\_features\_list, ave\_scores, "max\_features") # using the function to plot x and y values.

ave\_scores = [] # Creating a empty list

**for** single\_val **in** splitter\_list: # looping through each value in the list

model = DecisionTreeClassifier(splitter=single\_val) # creating an instance of a class.

scores = cross\_val\_score(model,X,y,cv=**5**) # Getting the results of the model.

ave\_scores.append(round(scores.mean(),**3**)) # getting the average score from the model and appending

# it to the ave\_scores list.

subplot(splitter\_list, ave\_scores, "splitter") # using the function to plot x and y values.

# X and y un\_edited

## Plotting the KNN's with a average Cross-val score

max\_depth\_list = [None,**1**,**2**,**3**,**4**,**5**,**6**,**7**,**8**,**9**,**10**,**25**,**50**,**75**,**80**,**90**,**100**,**125**,**150**,**175**,**200**,**225**,**250**,**275**,**300**,**500**] # a lsit with values

# specified.

min\_samples\_leaf\_list = list(range(**1**,**50**)) # a lsit with values specified.

min\_samples\_split\_list = list(range(**2**,**50**)) # a lsit with values specified.

min\_weight\_fraction\_leaf\_list = [**0.0**, **0.1**,**0.2**,**0.3**,**0.4**,**0.5**,**0.6**] # a lsit with values specified.

max\_leaf\_nodes\_list = [None,**10**,**20**,**30**,**40**,**50**,**60**,**70**,**80**,**90**,**100**,**125**, **150**,**175**, **200**,**225**,**250**,**275**,**300**] # a lsit with values specified.

min\_impurity\_decrease = [**0.0**] # a lsit with values specified.

criterion\_list = ["gini", "entropy"] # a lsit with values specified.

max\_features\_list = ["auto","log2","sqrt", None] # a lsit with values specified.

splitter\_list = ["best","random"] # a lsit with values specified.

DecisionTree\_plot\_Values(X,y, max\_depth\_list, min\_samples\_leaf\_list, min\_samples\_split\_list, min\_weight\_fraction\_leaf\_list, \

max\_leaf\_nodes\_list, criterion\_list,max\_features\_list, splitter\_list) # PLots Cross Val score

# Over Sampled X and y values

## Plotting the KNN's with a average Cross-val score

DecisionTree\_plot\_Values(X\_over,y\_over, max\_depth\_list, min\_samples\_leaf\_list, min\_samples\_split\_list, \

min\_weight\_fraction\_leaf\_list, max\_leaf\_nodes\_list, criterion\_list,max\_features\_list, splitter\_list) # PLots Cross

# Val score

# X and y obtained by using Corelation matrix

## Plotting the KNN's with a average Cross-val score

DecisionTree\_plot\_Values(X2,y, max\_depth\_list, min\_samples\_leaf\_list, min\_samples\_split\_list, min\_weight\_fraction\_leaf\_list, \

max\_leaf\_nodes\_list, criterion\_list,max\_features\_list, splitter\_list)

# PLots Cross Val score

# X and y un\_edited

# Without any model Tuning

crossvalscore(DecisionTreeClassifier(), X, y, **10**) # Performs cross validation.

# Using Cross Validation hyperparameter selection

msl\_list = [**32**, **33**, **34**] # a list of min\_samples\_leaf

mss\_list = [**31**, **29**] # a list of min\_samples\_split

**for** msl **in** msl\_list: # looping through a list

**for** mss **in** mss\_list: # looping through a list

**print**("Result when min\_samples\_leaf = ", msl) # printing output

**print**("Result when min\_samples\_split = ", mss) # printing output

crossvalscore(DecisionTreeClassifier(min\_samples\_leaf = msl, min\_samples\_split = mss, max\_leaf\_nodes = **10**, \

min\_weight\_fraction\_leaf = **0.0**, max\_depth = **4**, criterion = 'entropy', \

max\_features = "auto", splitter = "random"), X, y, **10**)

# gives Cross Val score

**print**("**\n**") # printing a new line

# Over Sampled X and y values

# Without any model Tuning

crossvalscore(DecisionTreeClassifier(), X\_over, y\_over, **10**)

# Performs cross validation.

# Using Cross Validation hyperparameter selection

crossvalscore(DecisionTreeClassifier(min\_samples\_leaf = **1**, min\_samples\_split = **2**, max\_leaf\_nodes = None, \

min\_weight\_fraction\_leaf = **0.0**, max\_depth = **125**, criterion = 'entropy', \

max\_features = None, splitter = "random"), X\_over, y\_over, **10**)

# Performs cross validation.

# X and y obtained by using Corelation matrix

# Without any model Tuning

crossvalscore(DecisionTreeClassifier(), X2, y, **10**) # Performs cross validation.

# Using Cross Validation hyperparameter selection

crossvalscore(DecisionTreeClassifier(min\_samples\_leaf = **10**, min\_samples\_split = **30**, max\_leaf\_nodes = **20**, \

min\_weight\_fraction\_leaf = **0.0**, max\_depth = **3**, criterion = 'entropy', \

max\_features = "sqrt", splitter = "random"), X2, y, **10**)

# Performs cross validation.

# X and y un\_edited

## Random search

max\_leaf\_nodes\_list = list(range(**1**,**20**)) # a lsit with values specified.

min\_samples\_leaf\_list = [**32**, **33**, **34**] # a lsit with values specified.

min\_samples\_split\_list = [**29**, **31**] # a lsit with values specified.

**for** i **in** range(len(min\_samples\_split\_list)):

**for** j **in** range(len(min\_samples\_leaf\_list)):

list1 = [] # creating a empty list

list2 = [] # creating a empty list

para\_rand = dict(max\_leaf\_nodes = max\_leaf\_nodes\_list, min\_samples\_leaf = [min\_samples\_leaf\_list[j]], \

min\_samples\_split = [min\_samples\_split\_list[i]]) # adding the above

# lists in a dictinary.

rand\_search = rand\_search\_fun(DecisionTreeClassifier(min\_weight\_fraction\_leaf = **0.0**, \

max\_depth = **4**, criterion = 'entropy', \

max\_features = "auto", splitter = "random"), \

para\_rand, **5**, X, y) # X and y un\_edite

## Random search # Using the grid search gunction with

**for** m **in** range(len(rand\_search.cv\_results\_["mean\_test\_score"])): # looping through the times

# the length of

# the mean\_test\_score

list1.append(rand\_search.cv\_results\_["mean\_test\_score"][m]) # appending the values to list

list2.append(rand\_search.cv\_results\_["param\_max\_leaf\_nodes"][m]) # appedning the

# values to the list2.

sorted\_list1= []

sorted\_list2 = list2.copy() # creating a copy of the list2 variables values.

sorted\_list2.sort() # sorting the list2

**for** k **in** range(len(sorted\_list2)): # Looping through the lenght of the sorted\_list2 variable.

**for** l **in** range(len(list2)): # Looping through the lenght of the list2 variable.

**if** sorted\_list2[k] == list2[l]: # checking that if the values of

# sorted\_list2[i] is equal to list2[j]

sorted\_list1.append(list1[l]) # appeding the list1[j] values to the sorted\_list1 list.

plt.figure(dpi=**100**, figsize=(**14**, **7**)) # setting the plot size

plt.title("Random Search Hyper parameter Comparison with "+str(min\_samples\_split\_list[i]) +" **\**

min samples split", fontsize=**25**, color="blue") # setting the plot title.

plt.plot(sorted\_list2,sorted\_list1 , "--", marker = "o", label="min samples leaf " \

+ str(min\_samples\_leaf\_list[j]), color="red") # setting the best

# variables values to the plot on the y axis and

# max depth on the x axis.

plt.xlabel('max leaf nodes',fontsize=**20**) # Setting the x label.

plt.ylabel("Avarage CV Score",fontsize=**20**) # setting the y label.

plt.legend(loc='upper left') # setting the legend.

plt.grid() # setting a grid

# Over Sampled X and y values

## Random search

max\_depth\_list = list(range(**101**,**150**)) # a lsit with values specified.

splitter\_list = ['best'] # a lsit with values specified.

para\_rand = dict(max\_depth = max\_depth\_list, splitter = splitter\_list) # adding the above

# lists in a dictinary.

rand\_search = rand\_search\_fun(DecisionTreeClassifier(min\_samples\_leaf = **1**, min\_samples\_split = **2**, max\_leaf\_nodes = None, \

min\_weight\_fraction\_leaf = **0.0**,criterion = 'entropy', \

max\_features = None), para\_rand, **5**, X\_over, y\_over)

# Using the random search function with

best = [] # creating a empty list

list1 = [] # creating a empty list

**for** i **in** range(len(rand\_search.cv\_results\_["mean\_test\_score"])): # looping through the times the length of

# the mean\_test\_score

best.append(rand\_search.cv\_results\_["mean\_test\_score"][i]) # appending the best values ot the

# best variable.

list1.append(rand\_search.cv\_results\_["param\_max\_depth"][i]) # appedning the values to the list1.

sorted\_best= [] # creating a empty list

sorted\_list1 = list1.copy() # creating a copy of the list1 variables values.

sorted\_list1.sort() # sorting the KNNs

**for** i **in** range(len(sorted\_list1)): # Looping through the lenght of the sorted\_list1 variable.

**for** j **in** range(len(list1)): # Looping through the lenght of the list1 variable.

**if** sorted\_list1[i] == list1[j]: # checking that if the values of sorted\_list1[i] is equal to list1[j]

sorted\_best.append(best[j]) # appeding the best[j] values to the sorted\_best list.

max\_depth\_list = list(range(**101**,**150**)) # a lsit with values specified.

splitter\_list = ['random'] # a lsit with values specified.

para\_rand = dict(max\_depth = max\_depth\_list, splitter = splitter\_list) # adding the above

# lists in a dictinary.

rand\_search = rand\_search\_fun(DecisionTreeClassifier(min\_samples\_leaf = **1**, min\_samples\_split = **2**, max\_leaf\_nodes = None, \

min\_weight\_fraction\_leaf = **0.0**,criterion = 'entropy', \

max\_features = None), para\_rand, **5**, X\_over, y\_over)

# Using the random search function with

random = [] # creating a empty list

list2 = [] # creating a empty list

**for** i **in** range(len(rand\_search.cv\_results\_["mean\_test\_score"])): # looping through the times the length of

# the mean\_test\_score

random.append(rand\_search.cv\_results\_["mean\_test\_score"][i]) # appending the random values ot the

# random variable.

list2.append(rand\_search.cv\_results\_["param\_max\_depth"][i]) # appedning the items to the list2.

sorted\_random = [] # creating a empty list

sorted\_list2 = list2.copy() # creating a copy of the list2 variables values.

sorted\_list2.sort() # sorting the list

**for** i **in** range(len(sorted\_list2)): # Looping through the lenght of the sorted\_list2 variable.

**for** j **in** range(len(list2)): # Looping through the lenght of the list2 variable.

**if** sorted\_list2[i] == list2[j]: # checking that if the values of sorted\_list2[i] equal list2[j]

sorted\_random.append(random[j]) # appeding the random[j] values to the sorted\_random list.

plt.figure(dpi=**100**, figsize=(**14**, **7**)) # setting the plot size

plt.title("Random Search Hyper parameter Comparison", fontsize=**25**, color="blue") # setting the plot title.

plt.plot(sorted\_list1,sorted\_best , "--", marker = "o", label="splitte best", color="red") # setting the best

plt.plot(sorted\_list2,sorted\_random ,":", marker = "\*", label="splitte random", color="blue") # setting the random

# variables values to the plot on the y axis and max depth on the x axis.

plt.xlabel('max depth',fontsize=**20**) # Setting the x label.

plt.ylabel("Avarage CV Score",fontsize=**20**) # setting the y label.

plt.legend(loc='upper left') # setting the legend.

plt.grid() # setting a grid

# X and y obtained by using Corelation matrix

## Random search

min\_samples\_split\_list = list(range(**2**,**50**)) # a lsit with values specified.

splitter\_list = ['best'] # a lsit with values specified.

para\_rand = dict(min\_samples\_split = min\_samples\_split\_list, splitter = splitter\_list) # adding the above

# lists in a dictinary.

rand\_search = rand\_search\_fun(DecisionTreeClassifier(min\_samples\_leaf = **10**, max\_leaf\_nodes = **20**, \

min\_weight\_fraction\_leaf = **0.0**, max\_depth = **3**, criterion = 'entropy', \

max\_features = "sqrt"), para\_rand, **5**, X2, y) # Using the grid search function with

best = [] # creating a empty list

list1 = [] # creating a empty list

**for** i **in** range(len(rand\_search.cv\_results\_["mean\_test\_score"])): # looping through the times the length of

# the mean\_test\_score

best.append(rand\_search.cv\_results\_["mean\_test\_score"][i]) # appending the best values ot the

# best variable.

list1.append(rand\_search.cv\_results\_["param\_min\_samples\_split"][i]) # appedning the values to the list1.

sorted\_best= [] # creating a empty list

sorted\_list1 = list1.copy() # creating a copy of the list1 variables values.

sorted\_list1.sort() # sorting the KNNs

**for** i **in** range(len(sorted\_list1)): # Looping through the lenght of the sorted\_list1 variable.

**for** j **in** range(len(list1)): # Looping through the lenght of the list1 variable.

**if** sorted\_list1[i] == list1[j]: # checking that if the values of sorted\_list1[i] is equal to list1[j]

sorted\_best.append(best[j]) # appeding the best[j] values to the sorted\_best list.

min\_samples\_split\_list = list(range(**2**,**50**)) # a lsit with values specified.

splitter\_list = ['random'] # a lsit with values specified.

para\_rand = dict(min\_samples\_split = min\_samples\_split\_list, splitter = splitter\_list) # adding the above

# lists in a dictinary.

rand\_search = rand\_search\_fun(DecisionTreeClassifier(min\_samples\_leaf = **10**, max\_leaf\_nodes = **20**, \

min\_weight\_fraction\_leaf = **0.0**, max\_depth = **3**, criterion = 'entropy', \

max\_features = "sqrt"), para\_rand, **5**, X2, y) # Using the grid search function with

random = [] # creating a empty list

list2 = [] # creating a empty list

**for** i **in** range(len(rand\_search.cv\_results\_["mean\_test\_score"])): # looping through the times the length of

# the mean\_test\_score

random.append(rand\_search.cv\_results\_["mean\_test\_score"][i]) # appending the random values ot the

# random variable.

list2.append(rand\_search.cv\_results\_["param\_min\_samples\_split"][i]) # appedning the items to the list2.

sorted\_random = [] # creating a empty list

sorted\_list2 = list2.copy() # creating a copy of the list2 variables values.

sorted\_list2.sort() # sorting the list

**for** i **in** range(len(sorted\_list2)): # Looping through the lenght of the sorted\_list2 variable.

**for** j **in** range(len(list2)): # Looping through the lenght of the list2 variable.

**if** sorted\_list2[i] == list2[j]: # checking that if the values of sorted\_list2[i] equal list2[j]

sorted\_random.append(random[j]) # appeding the random[j] values to the sorted\_random list.

plt.figure(dpi=**100**, figsize=(**14**, **7**)) # setting the plot size

plt.title("Random Search Hyper parameter Comparison", fontsize=**25**, color="blue") # setting the plot title.

plt.plot(sorted\_list1,sorted\_best , "--", marker = "o", label="splitte best", color="red") # setting the best

plt.plot(sorted\_list2,sorted\_random ,":", marker = "\*", label="splitte random", color="blue") # setting the random

# variables values to the plot on the y axis and max depth on the x axis.

plt.xlabel('min samples split',fontsize=**20**) # Setting the x label.

plt.ylabel("Avarage CV Score",fontsize=**20**) # setting the y label.

plt.legend(loc='upper left') # setting the legend.

plt.grid() # setting a grid

# X and y un\_edited

## Grid Search

max\_leaf\_nodes\_list = list(range(**1**,**20**)) # a list with values specified.

min\_samples\_leaf\_list = [**32**, **33**, **34**] # a list with values specified.

min\_samples\_split\_list = [**29**, **31**] # a list with values specified.

**for** i **in** range(len(min\_samples\_split\_list)):

**if** i == **0**:

para\_grid = dict(max\_leaf\_nodes = max\_leaf\_nodes\_list, min\_samples\_leaf = min\_samples\_leaf\_list, \

min\_samples\_split = [min\_samples\_split\_list[i]]) # adding the above

# lists in a dictinary.

grid\_search = Grid\_search\_fun(DecisionTreeClassifier(min\_weight\_fraction\_leaf = **0.0**, max\_depth = **4**, \

criterion = 'entropy', \

max\_features = "auto", splitter = "random"), para\_grid, **5**, X, y) # X and y un\_edited

**if** i == **1**:

para\_grid = dict(max\_leaf\_nodes = max\_leaf\_nodes\_list, min\_samples\_leaf = min\_samples\_leaf\_list, \

min\_samples\_split = [min\_samples\_split\_list[i]]) # adding the above

# lists in a dictinary.

grid\_search2 = Grid\_search\_fun(DecisionTreeClassifier(min\_weight\_fraction\_leaf = **0.0**, max\_depth = **4**, \

criterion = 'entropy', \

max\_features = "auto", splitter = "random"), para\_grid, **5**, X, y) # X and y un\_edited

## Random search # Using the grid search gunction with

list1 = [] # a empty list is created

**for** i **in** range(len(grid\_search.cv\_results\_["mean\_test\_score"])): # getting all even number

# indexes using a for loop.

**if** grid\_search.cv\_results\_["param\_min\_samples\_leaf"][i] == **32**:

list1.append(grid\_search.cv\_results\_["mean\_test\_score"][i]) # appending the 32 values to the

# varibale list1.

list2 = [] # a empty list is created

**for** i **in** range(len(grid\_search.cv\_results\_["mean\_test\_score"])): # getting all odd number indexes

# using a for loop.

**if** grid\_search.cv\_results\_["param\_min\_samples\_leaf"][i] == **33**:

list2.append(grid\_search.cv\_results\_["mean\_test\_score"][i]) # appending the 33 values to the

# varibale list2.

list3 = [] # a empty list is created

**for** i **in** range(len(grid\_search.cv\_results\_["mean\_test\_score"])): # getting all odd number indexes

# using a for loop.

**if** grid\_search.cv\_results\_["param\_min\_samples\_leaf"][i] == **34**:

list3.append(grid\_search.cv\_results\_["mean\_test\_score"][i]) # appending the 34 values to the

# varibale lst3.

plt.figure(dpi=**100**, figsize=(**14**, **7**)) # setting the plot size

plt.title("Grid Search Hyper parameter Comparison with 29 min samples split", fontsize=**25**, color="blue") # setting the

# plot title.

plt.plot(max\_leaf\_nodes\_list,list1 , "--", marker = "o", label="min samples leaf 32", color="red") # setting the best

plt.plot(max\_leaf\_nodes\_list,list2 ,":", marker = "\*", label="min samples leaf 33", color="blue") # setting the random

plt.plot(max\_leaf\_nodes\_list,list3 ,":", marker = "d", label="min samples leaf 34", color="orange") # setting the random

# variables values to the plot on the y axis and max depth on the x axis.

plt.xlabel('max leaf nodes',fontsize=**20**) # Setting the x label.

plt.ylabel("Avarage CV Score",fontsize=**20**) # setting the y label.

plt.legend(loc='upper left') # setting the legend.

plt.grid() # setting a grid

list1 = [] # a empty list is created

**for** i **in** range(len(grid\_search2.cv\_results\_["mean\_test\_score"])): # getting all even number

# indexes using a for loop.

**if** grid\_search2.cv\_results\_["param\_min\_samples\_leaf"][i] == **32**:

list1.append(grid\_search2.cv\_results\_["mean\_test\_score"][i]) # appending the 32 values to the

# varibale list1.

list2 = [] # a empty list is created

**for** i **in** range(len(grid\_search2.cv\_results\_["mean\_test\_score"])): # getting all odd number indexes

# using a for loop.

**if** grid\_search2.cv\_results\_["param\_min\_samples\_leaf"][i] == **33**:

list2.append(grid\_search2.cv\_results\_["mean\_test\_score"][i]) # appending the 33 values to the

# varibale list2.

list3 = [] # a empty list is created

**for** i **in** range(len(grid\_search2.cv\_results\_["mean\_test\_score"])): # getting all odd number indexes

# using a for loop.

**if** grid\_search2.cv\_results\_["param\_min\_samples\_leaf"][i] == **34**:

list3.append(grid\_search2.cv\_results\_["mean\_test\_score"][i]) # appending the 34 values to the

# varibale list3.

plt.figure(dpi=**100**, figsize=(**14**, **7**)) # setting the plot size

plt.title("Grid Search Hyper parameter Comparison with 31 min samples split", fontsize=**25**, color="blue") # setting the

# plot title.

plt.plot(max\_leaf\_nodes\_list,list1 , "--", marker = "o", label="min samples leaf 32", color="red") # setting the best

plt.plot(max\_leaf\_nodes\_list,list2 ,":", marker = "\*", label="min samples leaf 33", color="blue") # setting the random

plt.plot(max\_leaf\_nodes\_list,list3 ,":", marker = "d", label="min samples leaf 34", color="orange") # setting the random

# variables values to the plot on the y axis and max depth on the x axis.

plt.xlabel('max leaf nodes',fontsize=**20**) # Setting the x label.

plt.ylabel("Avarage CV Score",fontsize=**20**) # setting the y label.

plt.legend(loc='upper left') # setting the legend.

plt.grid() # setting a grid

# Over Sampled X and y values

## Grid Search

max\_depth\_list = list(range(**101**,**150**)) # a list with values specified.

splitter\_list = ['best', 'random'] # a list with values specified.

para\_grid = dict(max\_depth = max\_depth\_list, splitter = splitter\_list) # adding the above

# lists in a dictinary.

grid\_search = Grid\_search\_fun(DecisionTreeClassifier(min\_samples\_leaf = **1**, min\_samples\_split = **2**, max\_leaf\_nodes = None, \

min\_weight\_fraction\_leaf = **0.0**,criterion = 'entropy', \

max\_features = None), para\_grid, **5**, X\_over, y\_over) # Using the grid search gunction with

best = [] # a empty list is created

**for** i **in** range(len(grid\_search.cv\_results\_["mean\_test\_score"])): # getting all even number

# indexes using a for loop.

**if** grid\_search.cv\_results\_["param\_splitter"][i] == "best":

best.append(grid\_search.cv\_results\_["mean\_test\_score"][i]) # appending the best values to the

# varibale best.

random = [] # a empty list is created

**for** i **in** range(len(grid\_search.cv\_results\_["mean\_test\_score"])): # getting all odd number indexes

# using a for loop.

**if** grid\_search.cv\_results\_["param\_splitter"][i] == "random":

random.append(grid\_search.cv\_results\_["mean\_test\_score"][i]) # appending the random values to the

# varibale random.

plt.figure(dpi=**100**, figsize=(**14**, **7**)) # setting the plot size

plt.title("Grid Search Hyper parameter Comparison with ", fontsize=**25**, color="blue") # setting the plot title.

plt.plot(max\_depth\_list,best , "--", marker = "o", label="splitter best", color="red") # setting the best

plt.plot(max\_depth\_list,random ,":", marker = "\*", label="splitter random", color="blue") # setting the random

# variables values to the plot on the y axis and max depth on the x axis.

plt.xlabel('Max depth',fontsize=**20**) # Setting the x label.

plt.ylabel("Avarage CV Score",fontsize=**20**) # setting the y label.

plt.legend(loc='upper left') # setting the legend.

plt.grid() # setting a grid

# X and y obtained by using Corelation matrix

## Grid Search

min\_samples\_split\_list = list(range(**2**,**50**)) # a list with values specified.

splitter\_list = ['best', 'random'] # a list with values specified.

para\_grid = dict(min\_samples\_split = min\_samples\_split\_list, splitter = splitter\_list) # adding the above

# lists in a dictinary.

grid\_search = Grid\_search\_fun(DecisionTreeClassifier(min\_samples\_leaf = **10**, max\_leaf\_nodes = **20**, \

min\_weight\_fraction\_leaf = **0.0**, max\_depth = **3**, criterion = 'entropy', \

max\_features = "sqrt"), para\_grid, **5**, X2, y) # Using the grid search gunction with

best = [] # a empty list is created

**for** i **in** range(len(grid\_search.cv\_results\_["mean\_test\_score"])): # getting all even number

# indexes using a for loop.

**if** grid\_search.cv\_results\_["param\_splitter"][i] == "best":

best.append(grid\_search.cv\_results\_["mean\_test\_score"][i]) # appending the best values to the

# varibale best.

random = [] # a empty list is created

**for** i **in** range(len(grid\_search.cv\_results\_["mean\_test\_score"])): # getting all odd number indexes

# using a for loop.

**if** grid\_search.cv\_results\_["param\_splitter"][i] == "random":

random.append(grid\_search.cv\_results\_["mean\_test\_score"][i]) # appending the random values to the

# varibale random.

plt.figure(dpi=**100**, figsize=(**14**, **7**)) # setting the plot size

plt.title("Grid Search Hyper parameter Comparison with ", fontsize=**25**, color="blue") # setting the plot title.

plt.plot(min\_samples\_split\_list,best , "--", marker = "o", label="splitter best", color="red") # setting the best

plt.plot(min\_samples\_split\_list,random ,":", marker = "\*", label="splitter random", color="blue") # setting the random

# variables values to the plot on the y axis and max depth on the x axis.

plt.xlabel('min samples split',fontsize=**20**) # Setting the x label.

plt.ylabel("Avarage CV Score",fontsize=**20**) # setting the y label.

plt.legend(loc='upper left') # setting the legend.

plt.grid() # setting a grid

# X and y un\_edited

## Checking predicted/actual results

## Checking testing and traning scores

## Checking Actual values classified correctly and wrongly.

## Checking accuracy, precision, recall and f1 scores

Classifier\_function(DecisionTreeClassifier(min\_weight\_fraction\_leaf = **0.0**, max\_depth = **4**, criterion = 'entropy', \

max\_features = "auto", splitter = "random", max\_leaf\_nodes = **6**, \

min\_samples\_leaf = **33**, min\_samples\_split = **31**), X\_train, y\_train,X\_test,\

y\_test, "Decision Tree")

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Results after feature scaling

# StandardScaler

featurescaling(StandardScaler(), X\_train, X\_test, y\_train, y\_test,DecisionTreeClassifier(min\_weight\_fraction\_leaf = **0.0**,\

max\_depth = **4**, criterion = 'entropy', max\_features = "auto",\

splitter = "random", max\_leaf\_nodes = **6**,min\_samples\_leaf = **33**,\

min\_samples\_split = **31**) ,"Decision Tree")

# performs standard scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# MinMaxScaler

featurescaling(MinMaxScaler(), X\_train, X\_test, y\_train, y\_test, DecisionTreeClassifier(min\_weight\_fraction\_leaf = **0.0**,\

max\_depth = **4**, criterion = 'entropy', max\_features = "auto",\

splitter = "random", max\_leaf\_nodes = **6**,min\_samples\_leaf = **33**,\

min\_samples\_split = **31**) ,"Decision Tree")

# performs Minmax scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# RobustScaler

featurescaling(RobustScaler(), X\_train, X\_test, y\_train, y\_test,DecisionTreeClassifier(min\_weight\_fraction\_leaf = **0.0**,\

max\_depth = **4**, criterion = 'entropy', max\_features = "auto",\

splitter = "random", max\_leaf\_nodes = **6**,min\_samples\_leaf = **33**,\

min\_samples\_split = **31**) ,"Decision Tree")

# performs robust scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Normalizer

featurescaling(Normalizer(), X\_train, X\_test, y\_train, y\_test, DecisionTreeClassifier(min\_weight\_fraction\_leaf = **0.0**,\

max\_depth = **4**, criterion = 'entropy', max\_features = "auto",\

splitter = "random", max\_leaf\_nodes = **6**,min\_samples\_leaf = **33**,\

min\_samples\_split = **31**) ,"Decision Tree")

# Performs normalization scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Over Sampled X and y values

# Without any model Tuning

## Checking predicted/actual results

## Checking testing and traning scores

## Checking Actual values classified correctly and wrongly.

## Checking accuracy, precision, recall and f1 scores

Classifier\_function(DecisionTreeClassifier(min\_samples\_leaf = **1**, min\_samples\_split = **2**, max\_leaf\_nodes = None, \

min\_weight\_fraction\_leaf = **0.0**,criterion = 'entropy', max\_features = None, \

max\_depth = **121**, splitter = 'random'), X\_train\_over, y\_train\_over, X\_test\_over,\

y\_test\_over, "Decision Tree")

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Feature scaling

# StandardScaler

featurescaling(StandardScaler(), X\_train\_over, X\_test\_over, y\_train\_over, \

y\_test\_over,DecisionTreeClassifier(min\_samples\_leaf = **1**, min\_samples\_split = **2**,\

max\_leaf\_nodes = None, min\_weight\_fraction\_leaf = **0.0**,criterion = 'entropy', max\_features = None, \

max\_depth = **121**, splitter = 'random'), "Decision Tree")

# performs standard scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# MinMaxScaler

featurescaling(MinMaxScaler(), X\_train\_over, X\_test\_over, y\_train\_over,\

y\_test\_over,DecisionTreeClassifier(min\_samples\_leaf = **1**, min\_samples\_split = **2**,\

max\_leaf\_nodes = None, min\_weight\_fraction\_leaf = **0.0**,criterion = 'entropy', max\_features = None, \

max\_depth = **121**, splitter = 'random') ,"Decision Tree")

# performs Minmax scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# RobustScaler

featurescaling(RobustScaler(), X\_train\_over, X\_test\_over, y\_train\_over,\

y\_test\_over,DecisionTreeClassifier(min\_samples\_leaf = **1**, min\_samples\_split = **2**,\

max\_leaf\_nodes = None, min\_weight\_fraction\_leaf = **0.0**,criterion = 'entropy', max\_features = None, \

max\_depth = **121**, splitter = 'random') ,"Decision Tree")

# performs robust scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Normalizer

featurescaling(Normalizer(), X\_train\_over, X\_test\_over, y\_train\_over,\

y\_test\_over,DecisionTreeClassifier(min\_samples\_leaf = **1**, min\_samples\_split = **2**,\

max\_leaf\_nodes = None, min\_weight\_fraction\_leaf = **0.0**,criterion = 'entropy', max\_features = None, \

max\_depth = **121**, splitter = 'random') ,"Decision Tree")

# Performs normalization scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# X and y obtained by using Corelation matrix

# Without any model Tuning

## Checking predicted/actual results

## Checking testing and traning scores

## Checking Actual values classified correctly and wrongly.

## Checking accuracy, precision, recall and f1 scores

Classifier\_function(DecisionTreeClassifier(min\_samples\_leaf = **10**, max\_leaf\_nodes = **20**, min\_weight\_fraction\_leaf = **0.0**,\

max\_depth = **3**, criterion = 'entropy',max\_features = "sqrt",\

min\_samples\_split = **2**, splitter = 'best'), X2\_train, y2\_train,X2\_test, \

y2\_test, "Decision Tree")

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Results

# Original Results without hyperparameter Improvement

Classifier\_function(DecisionTreeClassifier(), X\_train\_over, y\_train\_over, X\_test\_over, y\_test\_over, "Decision Tree")

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Best Score and model

# Over Sampled X and y values

# MinMaxScaler

# Results with hyparameters improved

featurescaling(MinMaxScaler(), X\_train\_over, X\_test\_over, y\_train\_over,\

y\_test\_over,DecisionTreeClassifier(min\_samples\_leaf = **1**, min\_samples\_split = **2**,\

max\_leaf\_nodes = None, min\_weight\_fraction\_leaf = **0.0**,criterion = 'entropy', max\_features = None, \

max\_depth = **121**, splitter = 'random') ,"Decision Tree")

# performs Minmax scaling

# Performs traing, testing prediction.

# performs precision, recall, f1-score and support prediction

# plots a confusion matrix

# returns the traing, testing, precision, recall, f1-score

# Un\_edited full model evaluation

crossvalscore(DecisionTreeClassifier(), X\_over, y\_over, **10**) # Performs cross validation.

# Improved model full Evaluation with feature scaling

crossvalscore(DecisionTreeClassifier(min\_samples\_leaf = **1**, min\_samples\_split = **2**,\

max\_leaf\_nodes = None, min\_weight\_fraction\_leaf = **0.0**,criterion = 'entropy', max\_features = None, \

max\_depth = **121**, splitter = 'random'), X\_over, y\_over, **10**) # Performs cross validation.

# Overall results and full evaluation

**def** **plot\_graph**(list\_for\_plot, list\_for\_plot2,Accuracy\_type, colour): # funstion with given parameters.

"""

The function plot\_graph plots a lineargraph.

The first parameter list\_for\_plot is the x axis.

The second parameter list\_for\_plot2 is the y axis.

The third parameter Accuracy\_type takes a string.

for example "F1 score"

The fourth parameter colour is the color for the bar plot.

"""

plt.figure() # plots figure

plt.title("Model Evaluation",fontsize=**18**) # Displays plot title

plt.plot(list\_for\_plot, list\_for\_plot2, color = colour) # Displays description of the plots x and y labels.

plt.xlabel("Models") # Displays the x axis for the plot

plt.ylabel(Accuracy\_type) # Displays the y axis for the plot.

plt.grid() # adds a gird to the plot

## k-fold cross-validation

**def** **crossvalscore**(model, X, y, cv\_val): # function to perform cross validation with model X, y and cv\_val as parameters

"""

The crossvalscore function finds the avarage cross validation accuracy, precison, recall, f1 score, and area uner the curve

of a model and its standard deveation.

The first parameter model is the type of model to perform the cross validation on.

The second parameter X is the features.

The third parameter y is the labels.

the foruth parameter cv\_val is the number of times to cross validate the given model.

The crossvalscore function returns the cross validation accuracy, precison, recall, f1 scoer, and area uner the curve

"""

sc = MinMaxScaler() # creating an instance of the object.

X[:, **55**:] = sc.fit\_transform(X[:, **55**:]) # Scaling x\_train

X[:,**55**:] = sc.transform(X[:, **55**:]) # Scaling y\_train

scoring = ['accuracy', 'precision\_macro', 'recall\_macro', 'f1\_macro', 'roc\_auc\_ovr'] # a list with values given.

results = [] # a empty list

results\_std = []

**for** i **in** range(len(scoring)): # looping to the leghth of the variable scoring

**print**("score metric = ", scoring[i]) # printing output

score = cross\_val\_score(estimator = model, X = X, y = y,scoring=scoring[i], cv = cv\_val) # performs different tests to get best accurecy.

**print**("Score : ",score.mean()) # accuracy printed.

**print**("Standard Deviation", score.std()) # standard deveation printed (std -avarage or std+ avarage )

results.append(score.mean())

results\_std.append(score.std())

**print**("**\n**")

**return** results[**0**], results\_std[**0**], results[**1**],results\_std[**1**] ,results[**2**],results\_std[**2**],\

results[**3**],results\_std[**3**], results[**4**], results\_std[**4**]

# Decision Tree

DT\_accuracy,DT\_accuracy\_std, DT\_precision, DT\_precision\_std, DT\_recall,DT\_recall\_std, DT\_f1, DT\_f1\_std, DT\_auc, DT\_auc\_std = crossvalscore(DecisionTreeClassifier(min\_samples\_leaf = **1**, min\_samples\_split = **2**,\

max\_leaf\_nodes = None, min\_weight\_fraction\_leaf = **0.0**,criterion = 'entropy', max\_features = None, \

max\_depth = **121**, splitter = 'random'), X\_over, y\_over, **10**) # Performs cross validation.

# Random Forest

RF\_accuracy,RF\_accuracy\_std, RF\_precision, RF\_precision\_std, RF\_recall,RF\_recall\_std, RF\_f1, RF\_f1\_std, RF\_auc, RF\_auc\_std = crossvalscore(RandomForestClassifier(n\_estimators =**90**,min\_samples\_split = **2**, min\_samples\_leaf = **1**,\

max\_depth = **50**,bootstrap = False, max\_features = 'sqrt', criterion = 'entropy'), X\_over, y\_over, **10**)

# Performs cross validation.

# KNN

KNN\_accuracy,KNN\_accuracy\_std, KNN\_precision, KNN\_precision\_std, KNN\_recall,KNN\_recall\_std, KNN\_f1, KNN\_f1\_std, KNN\_auc, KNN\_auc\_std = crossvalscore(KNeighborsClassifier(n\_neighbors = **15**, weights ='distance'), X\_over, y\_over, **10**) # Performs cross validation.

model\_name = ["KNN","Decision Tree", "Random Forest"] # a list of models used.

Sampling = ["Over Sampled", "Over Sampled", "Over Sampled"] # a list of sampling techniwues used.

scalars = ["MInMax Scalar", "MinMax Scalar", "MinMax Scalar"] # a list of types of scaling techniques used.

mean\_accuracy = [KNN\_accuracy,DT\_accuracy,RF\_accuracy] # a list of model train accuracy

standard\_deaviation = [KNN\_accuracy\_std,DT\_accuracy\_std,RF\_accuracy\_std] # a list of model train standard deveation.

mean\_precision = [KNN\_precision,DT\_precision,RF\_precision] # a list of model precision score

precision\_standard\_deaviation = [KNN\_precision\_std,DT\_precision\_std,RF\_precision\_std] # a list of model precision standard deveation.

mean\_recall = [KNN\_recall,DT\_recall,RF\_recall] # a list of model recall score

recall\_standard\_deaviation = [KNN\_recall\_std,DT\_recall\_std,RF\_recall\_std] # a list of model recall standard deveation.

mean\_f1\_score = [KNN\_f1,DT\_f1,RF\_f1] # a list of model f1 score

f1\_score\_standard\_deaviation = [KNN\_f1\_std,DT\_f1\_std,RF\_f1\_std] # a list of model f1 score standard deveation.

mean\_Area\_under\_curve = [KNN\_auc,DT\_auc,RF\_auc] # a list of model area under curve score

Area\_under\_curve\_standard\_deaviation = [KNN\_auc\_std,DT\_auc\_std,RF\_auc\_std] # a list of model area under curve standard deveation.

Evaluation = pd.DataFrame({

'Model':model\_name,

'Sampling': Sampling,

'scalar type':scalars,

'Mean\_accuracy':mean\_accuracy,

'Mean Accuracy Standard Deaviation':standard\_deaviation ,

'Mean Precision':mean\_precision,

'Precision Standard Deaviation':precision\_standard\_deaviation ,

'Mean Recall':mean\_recall,

'Recall Standard Deaviation':recall\_standard\_deaviation ,

'Mean f1 score':mean\_f1\_score,

'f1 score Standard Deaviation':f1\_score\_standard\_deaviation ,

'Mean Area under curve':mean\_Area\_under\_curve,

'Area under curve Standard Deaviation':Area\_under\_curve\_standard\_deaviation

}) # using lists to make a dataframe

Evaluation # viewing dataframe information

Evaluation.sort\_values(by='Mean f1 score', ascending=False) # viewing dataframe information by f1 score in decending order.

Evaluation.sort\_values(by='Mean Recall', ascending=False) # viewing dataframe information by recall in decending order.

Evaluation.sort\_values(by='Mean Area under curve', ascending=False) # viewing dataframe information by area under the curve

# in decending order.

plot\_bar\_graph(model\_name, mean\_f1\_score, "f1 score", "red") # functions argents given. plots output using given data.

plot\_bar\_graph(model\_name, mean\_recall, "Recall", "blue") # functions argents given. plots output using given data.

plot\_graph(model\_name, mean\_Area\_under\_curve, "Area Under Curve", "black") # functions argents given. plots output

# using given data.

plot\_graph(model\_name, mean\_f1\_score, "f1\_score", "black") # functions argents given. plots output using given data.

plot\_graph(model\_name, mean\_recall, "recall", "black") # functions argents given. plots output using given data.

>

# Appendix C

## Outlier analysis

The outliers in this dataset are present in the Population, Total Labour force, GDPpyear, GDPpcapita, Ref ugee\_population\_by\_country\_or\_territory\_of\_origin and Suicidesper100k columns. The data in these columns is taken from 48 countries in years 1985 to 2016 from different age groups and genders. As seen by Figure 1 Countries that Mongolia has only 10 samples while Mexico has 372 samples and looking at Figure 3 Population it is observed that the population of males aged 75+ is 36300 and looking at Figure 2 Population the average population is 3035752.0 there is a 195.274% difference between these two numbers. Judging by these numbers alone it can be seen that there would be outliers present in the data set.

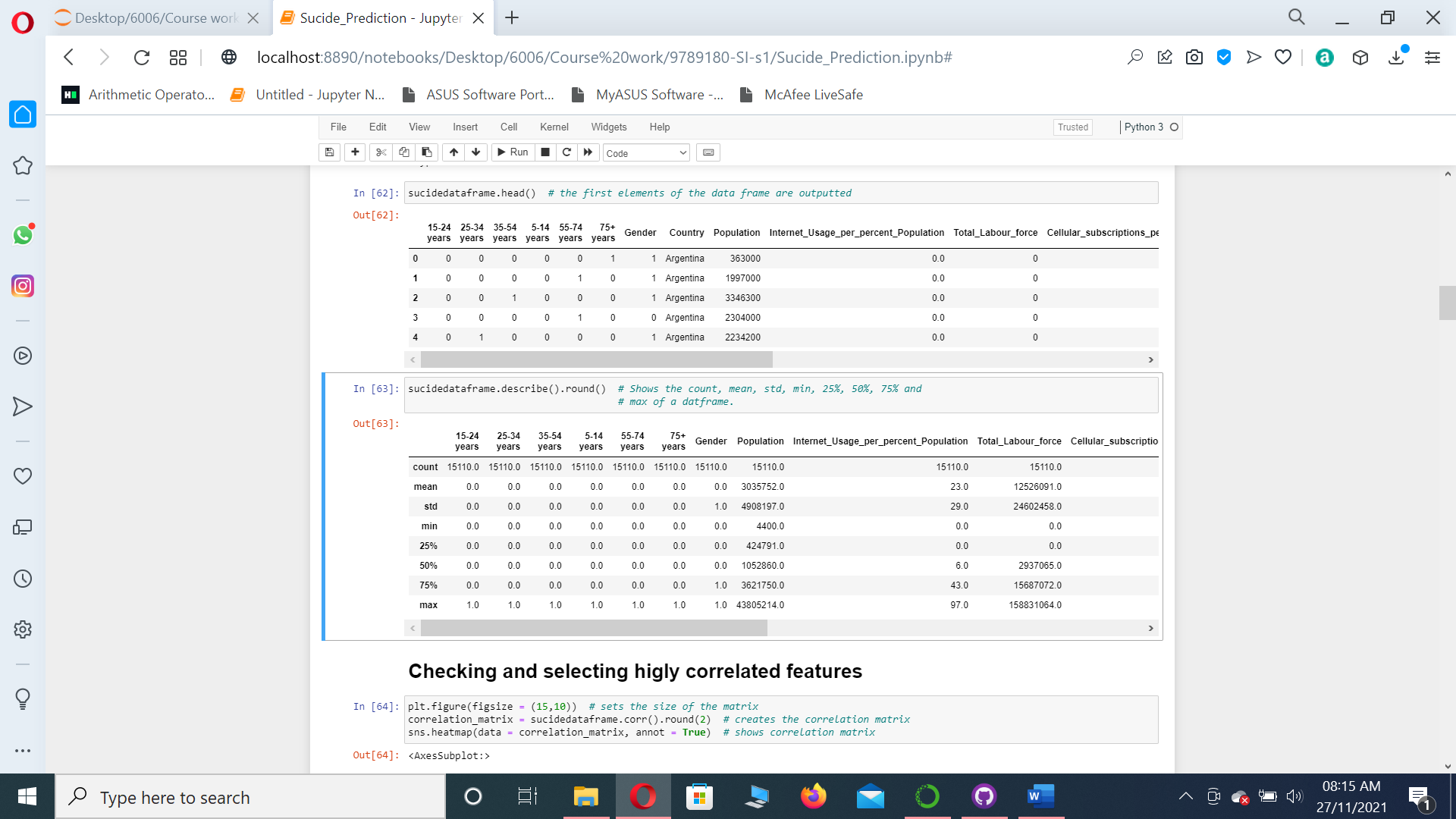


Figure 8 Population

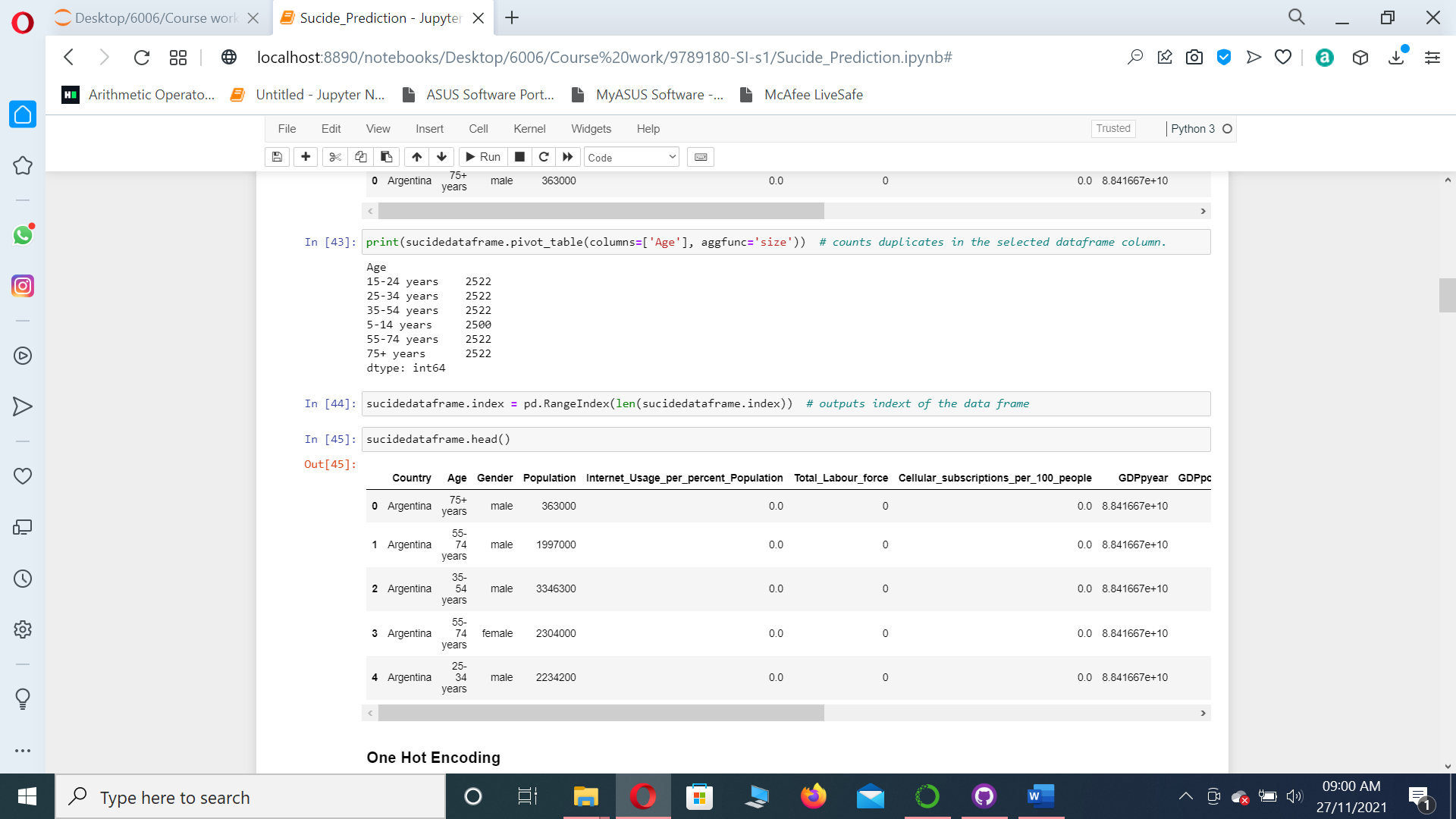


Figure 9 Population

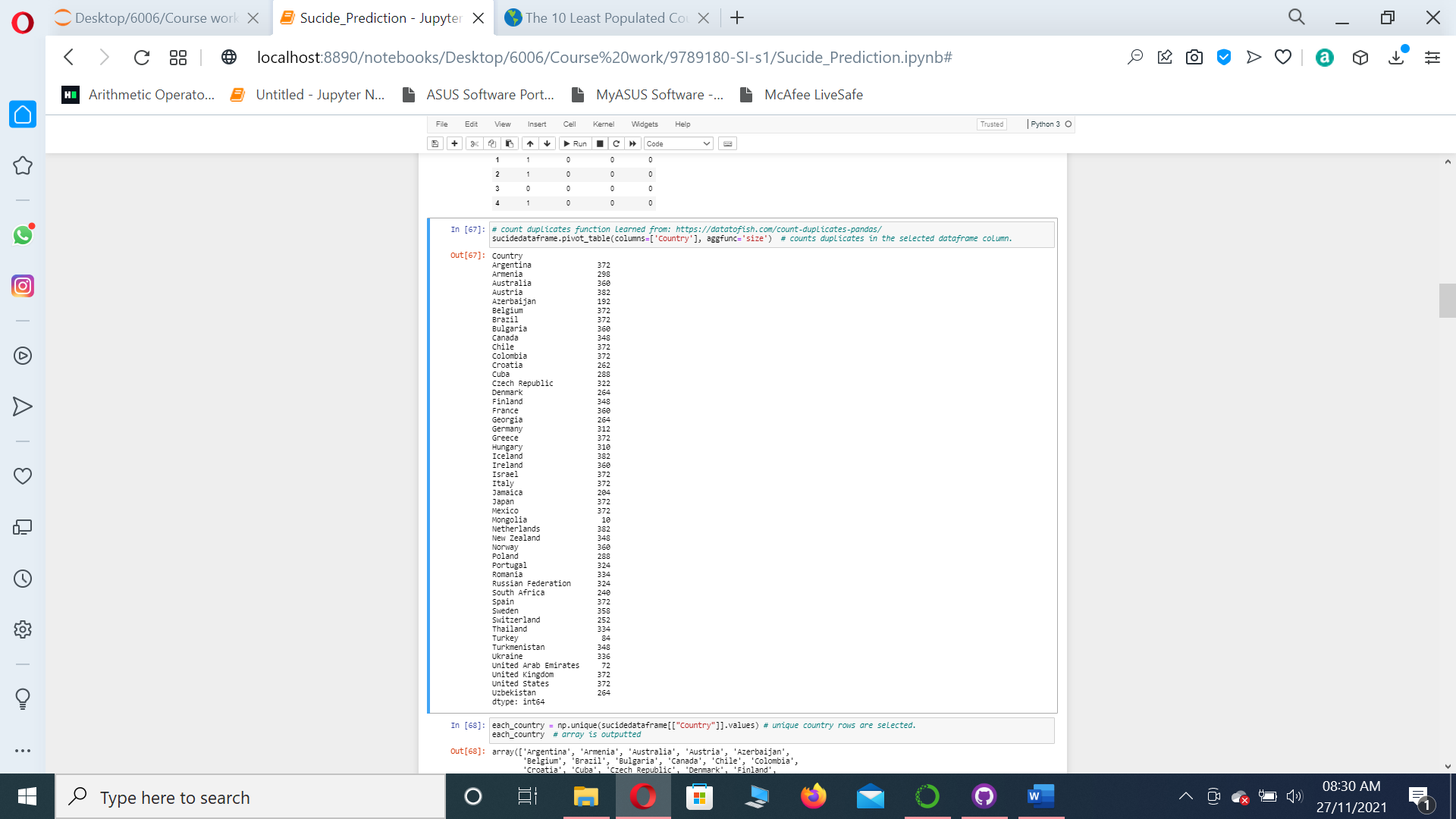
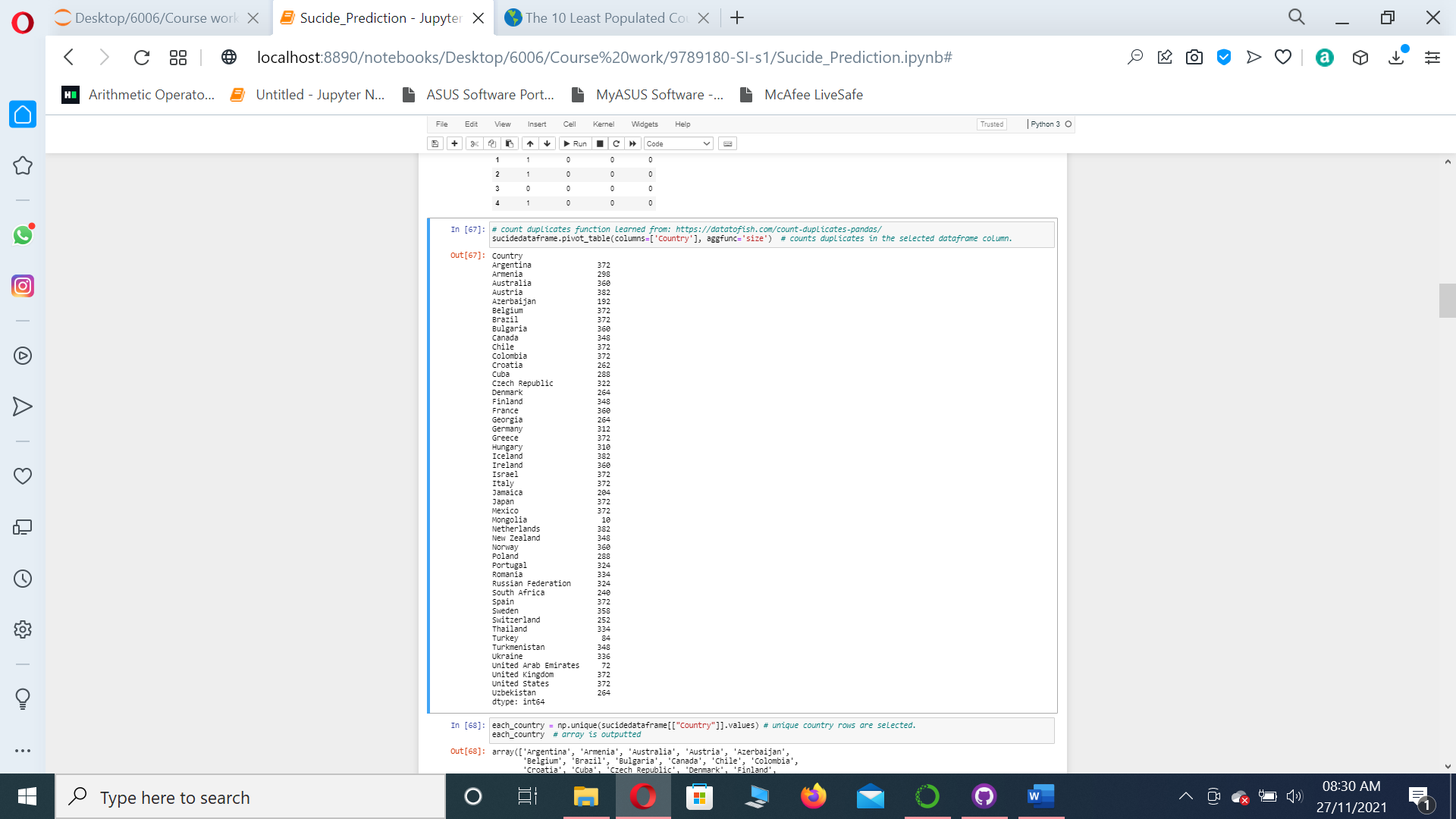


Figure 10 Countries

Now as seen on Figure 4 population by age there is a marginal difference between people aged between 5 – 14 and 13 – 24 from all other aged groups. Which can also indicate outliers but the information does add value to the data analysis.

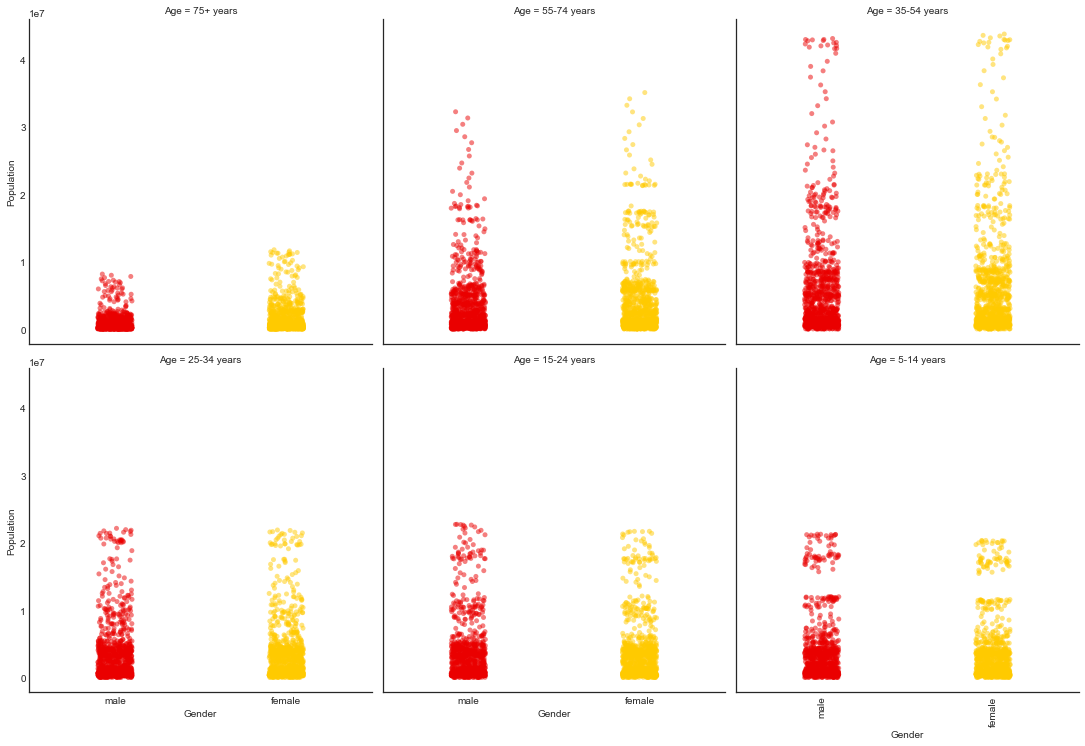


Figure 11 population by age

Observing Figure 5 Suicide by population a observation can be made that males aged 75 + have the highest suicide and males aged 35 – 54 have the highest suicide rate but with a increase in population over 20000000 the suicide levels stop increasing and become steady. Indicating the presence of outliers. which is the same case for people aged 55 – 74.

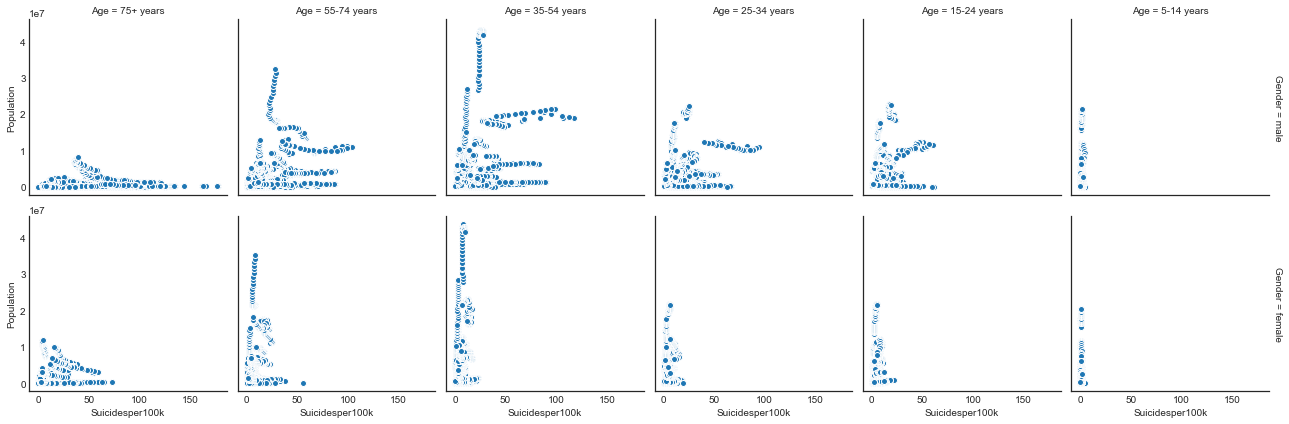


Figure 12 Suicide by population

Observing Figure 6 Refugee\_population\_by\_country\_or\_territory\_of\_origin the rate of sucide in counties with lower refugees is higher as compared to countries with more refugees for males.

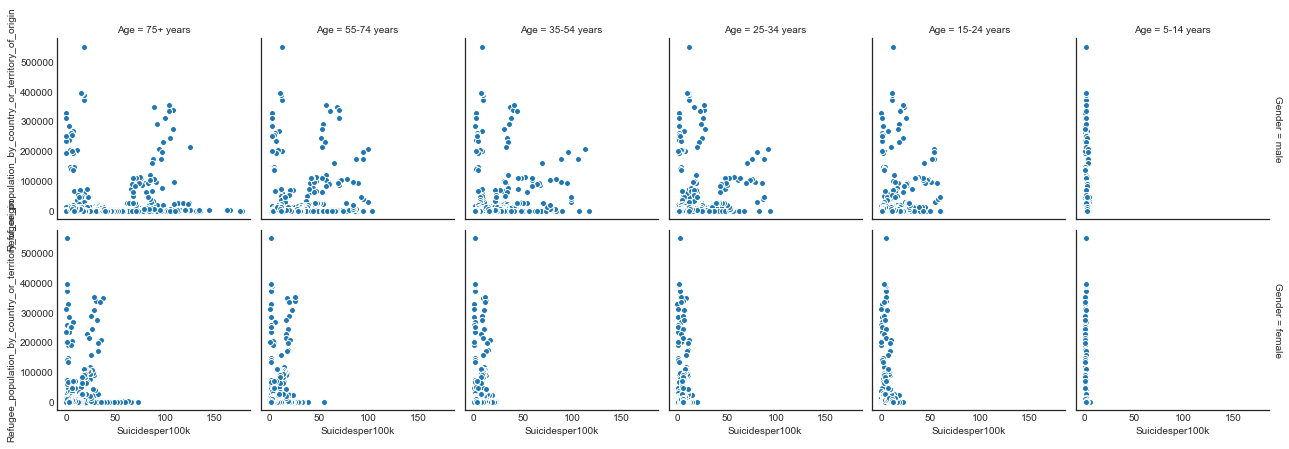


Figure 13 Refugee\_population\_by\_country\_or\_territory\_of\_origin by suicide

Looking at figure Figure 7 GDP per year by suicide it is seen that the number of suicides decrease as the GDP per year of a county increases.

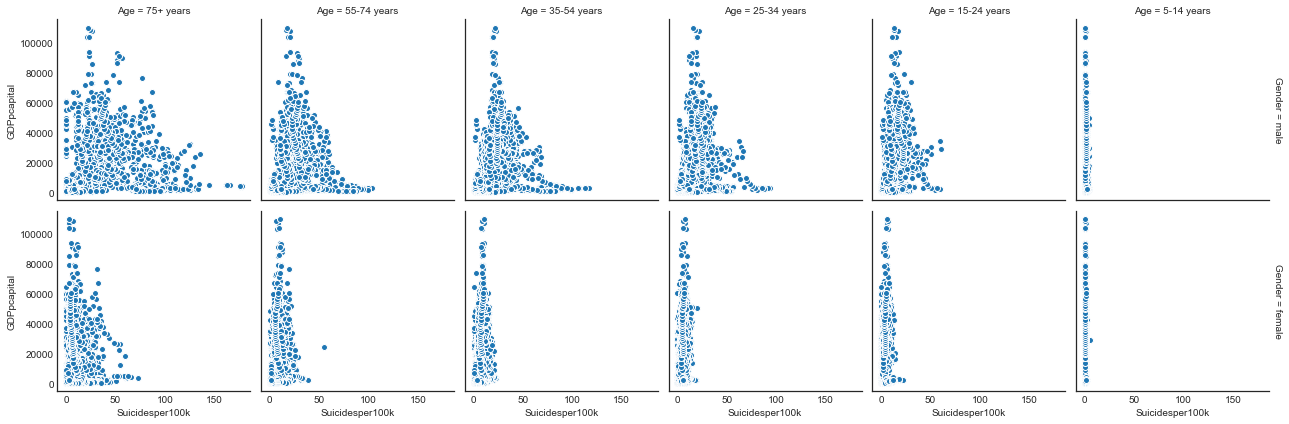


Figure 14 GDP per year by suicide

Although the data is from different counties and different age groups a trend is seen that countries with a higher population and higher refugees the counties also have a higher GDP and so it makes sense that wealthier counties would have more refugees and better quality of life and so lower suicide rate. They are many extreme low values and extreme high values but as observed above the data is from various age ranges , countries and is indicating a pattern so the outliers are providing value to the dataset as they are following clear trend and hence they will be kept for this project.

# Appendix D

## Suicide Label Classification

The maximum number of suicides being 178 see Figure 2 Suicide rate assessment were divided by 2 then rounded and 89 was obtained. Number of suicides between 89 to 178 were decided as maximum chances of suicide and were labelled as 5. Then 89 was again divided by 2 giving the number then rounded giving 44. The number of suicides between 44 to 89 were classified as high-risk suicides and were labelled as 4. The number 44 was again divided by 2 giving the number 22. The rage between 22 and 44 was selected as medium risk suicide and labelled as 3. The number 22 was again divided by 2 giving the number 11. The rage of suicides between 11 and 22 were classified as low risk of suicide and were labelled as 2. Then finally the number of suicides below 11 were classified as minimum risk of suicide and were labelled as 1.

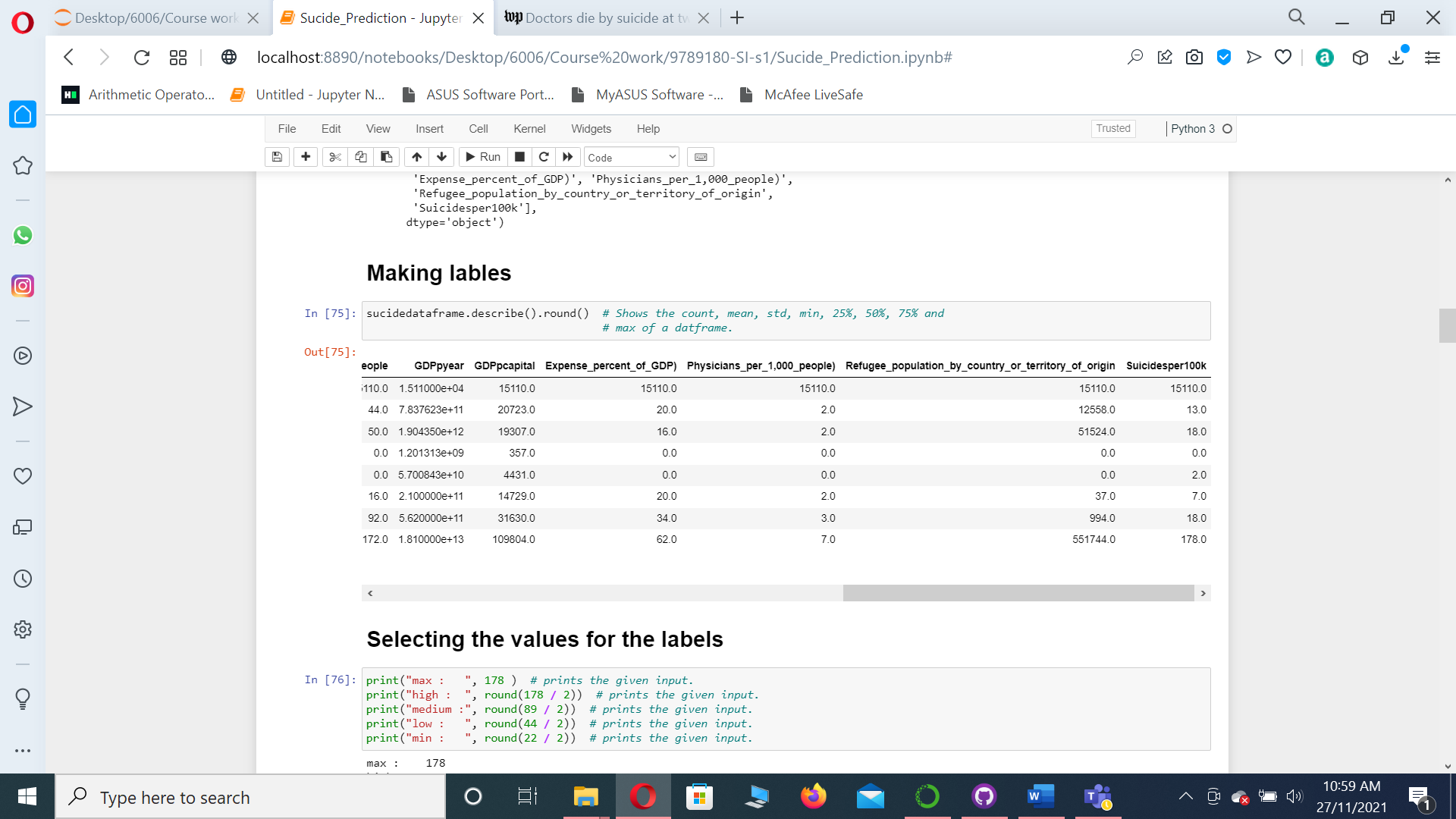
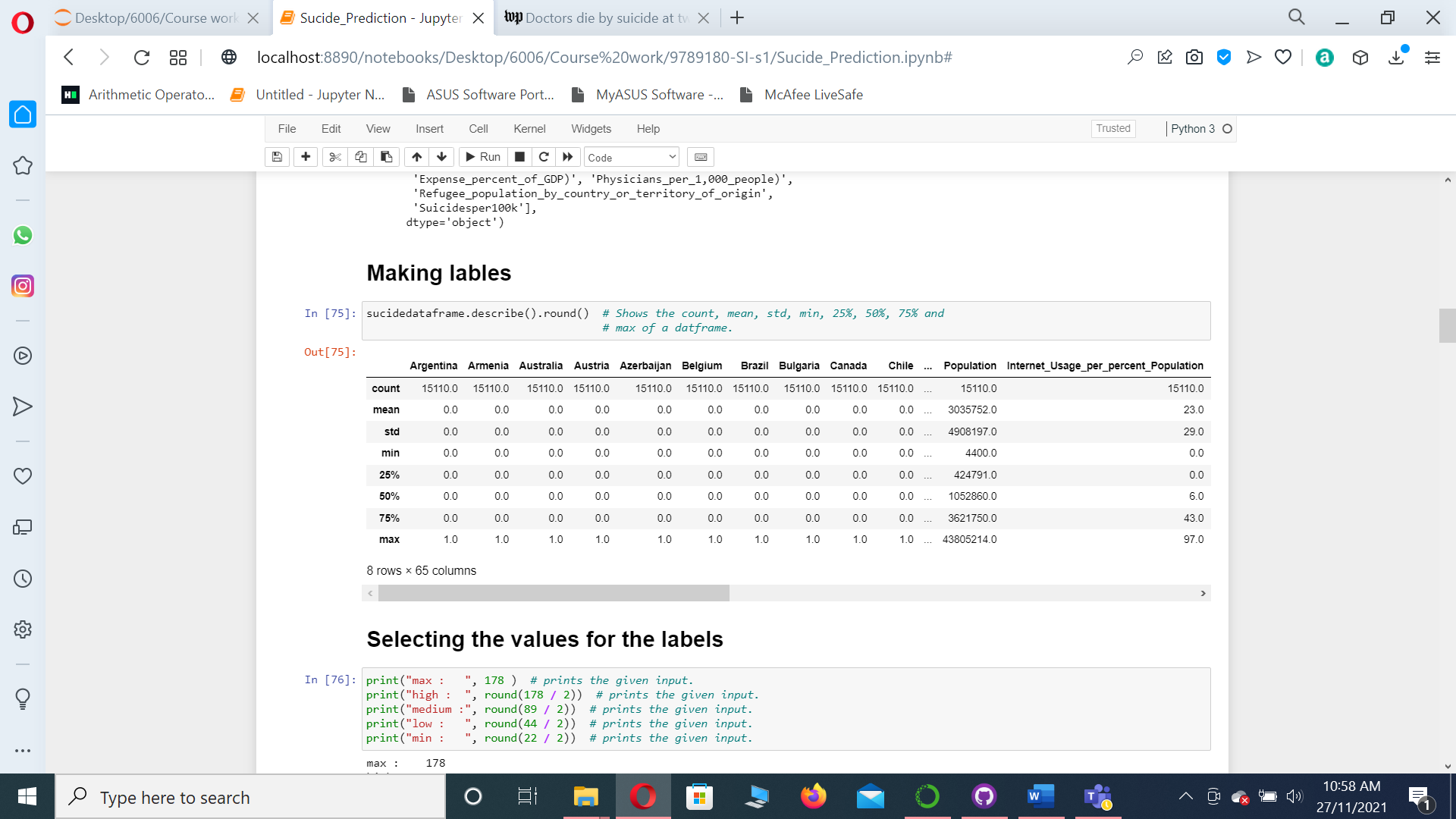


Figure 15 Suicide rate assessment

# Appendix E

## Model optimization

As the models performed using the oversampled best feature the best so only those model optimization techniques will be mentioned here. Other optimization of the default and the set of label and features obtained using confusing matrix can be found online at: <https://github.coventry.ac.uk/iftikhars/9789180-SI-s1>

### KNN

### KNN with hyperparameters optimized using different neighbours and weight set as distance

When preforming cross validation to improve model hyperparameters 1 neighbour with weight distance was determined to give the best results.

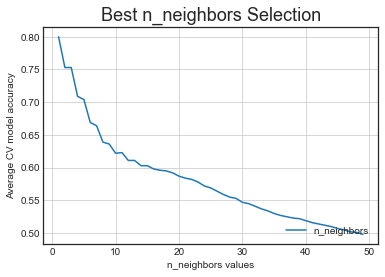


Figure 16 KNN Cross Validation

When preforming Random search to improve model hyperparameters 3 neighbour with weight distance was determined to give the best results.

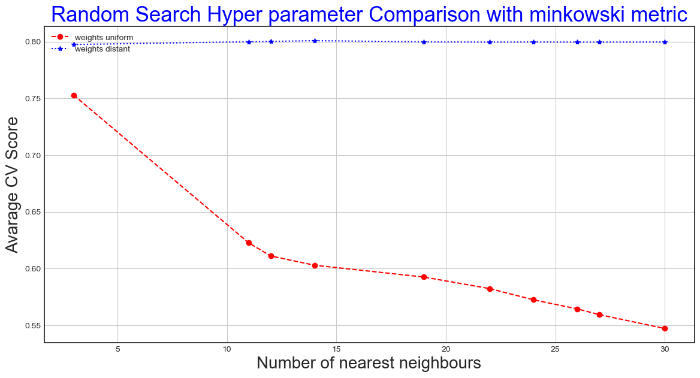


Figure 17 KNN Random Search

When preforming Grid search to improve model hyperparameters 15 neighbours with weight distance was determined to give the best results.

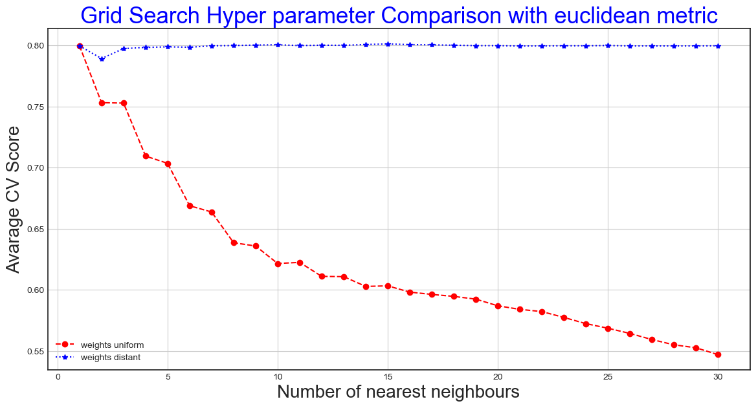


Figure 18 KNN Grid Search

The hyperparameters metrics algorithms and leaf\_size had no effect on the above models performance improvement so they were kept as default.

With 1 neighbour using standard scalar it had 99 % accuracy, 99 % precision, 99% recall, 99 % f1 score with 0.9910556787942809 % area under the curve.

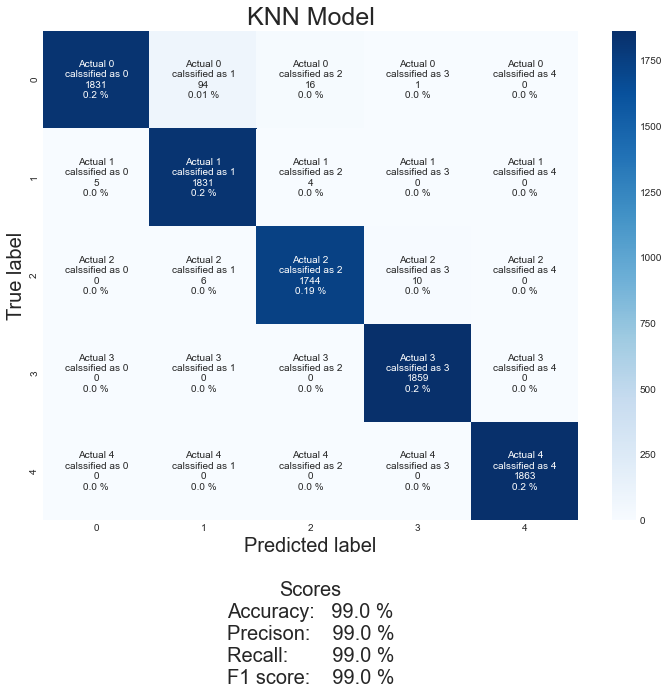


Figure 19 KNN Standardscalar

With 1 neighbour using MinMaxScalar on the features it had 99 % accuracy, 99 % precision, 99% recall, 99 % f1 score with 0.9920822625129446 % area under the curve.



Figure 20 KNN MinMax1

With 3 neighbour using MinMaxScalar on the features it had 99 % accuracy, 99 % precision, 99% recall, 99 % f1 score with 0.9942384129273425 % area under the curve.

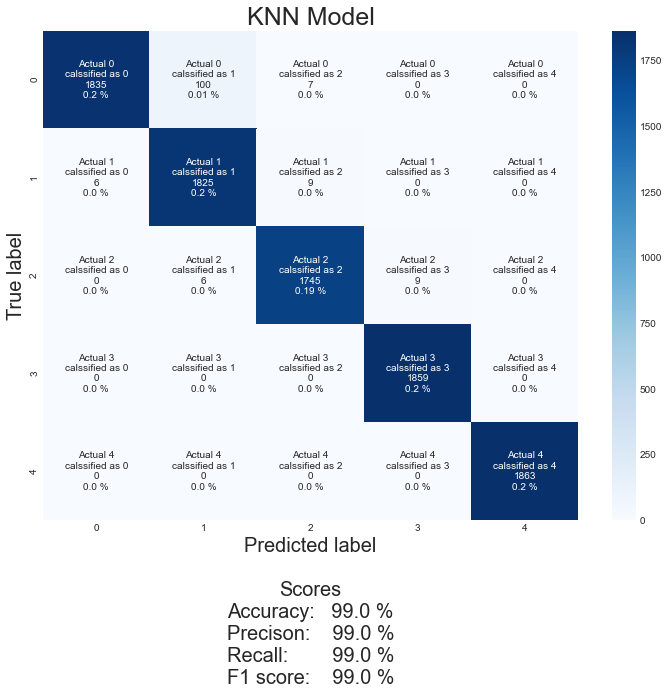


Figure 21 KNN MinMax3

With 1 neighbour using Normalizer on the features it had 99 % accuracy, 99 % precision, 99% recall, 99 % f1 score with 0.9921664206004255 % area under the curve.

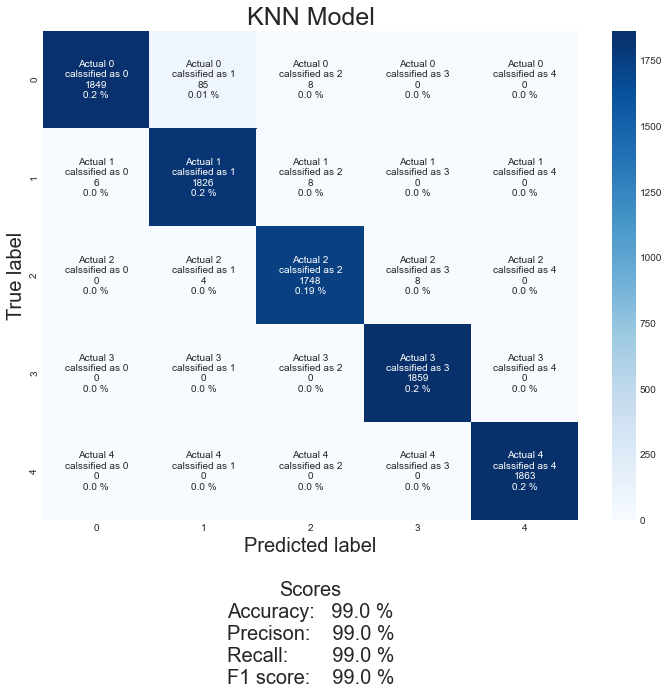


Figure 22 KNN Normalizer

With 3 neighbour using Normalizer it had 99 % accuracy, 99 % precision, 99% recall, 99 % f1 score with 0.9941760974789513 % area under the curve.

As it can be seen that With 3 neighbour using MinMaxScalar it had 99 % accuracy, 99 % precision, 99% recall, 99 % f1 score with 0.9942384129273425 % area under the curve. But the model is further evaluated with cross validation with the different neighbours to find the best neighbours.

When evaluated with cross validation the on the default training and testing set 71.71 % accuracy and 2.11 % standard deviation were achieved.

When evaluated with cross validation it performed best using 15 neighbours, weight set as distance with 80.22 % accuracy and 1.40 % standard deviation.

When evaluated with cross validation it performed best using 3 neighbours, weight set as distance with 79.96 % accuracy and 1.43 % standard deviation.

When evaluated with cross validation it performed best using 1 neighbour, weight set as distance with 80.28 % accuracy and 2.05 % standard deviation.

When considering the accuracy alone KNN with 1 neighbour performs better but when considering the standard deviation, the 15 neighbours outperform the 1 neighbour and perform better .

15 neighbours will be selected for the KNN model as hyperparameters for the final evaluation with uniform weight.

### Random Forest

#### Random forest with hyperparameters optimized

Random forest n\_estimators hyperparameters were firstly tuned using cross validation in a given range of numbers.

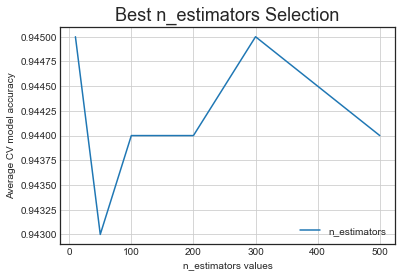


Figure 23 Random Forest Cross Validation 1

The range is narrowed down and the hyperparameter is further improved.

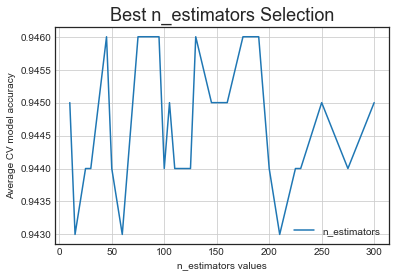


Figure 24 Random Forest Cross Validation 2

Random forest Max\_depth hyperparameters were firstly tuned using cross validation in a given range of numbers.

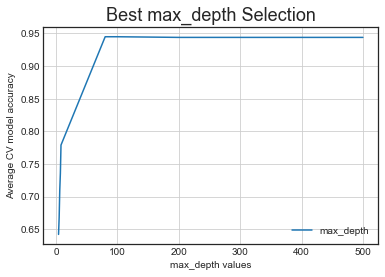


Figure 25 Random Forest Cross Validation 3

The range is narrowed down and the hyperparameter is further improved.



Figure 26 Random Forest Cross Validation 4

As Random forest is computationally very heavy so a lower value of the hyperparameters n\_estimators with max\_depth was perfred to decrease the computation time. Cross validation tests are run using these hyperparameters and it is determined that 90 n\_estimators with max\_depth 50 gives the best results.

1 min\_samples\_leaf was selected as the best hyperparameter using cross validation.

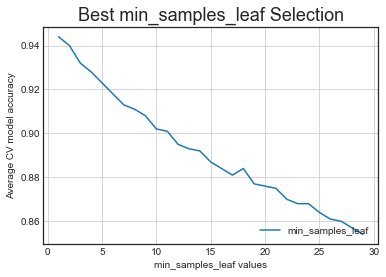


Figure 27 Random Forest Cross Validation 5

2 and 3 min\_samples\_split was selected as the best hyperparameter using cross validation.

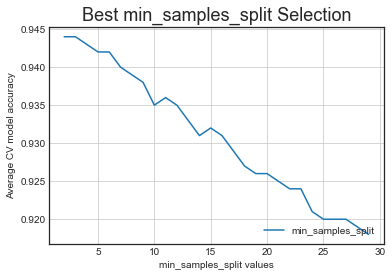


Figure 28 Random Forest Cross Validation 6

The min\_samples\_split were further tested using cross validation and it was determined that 2 min\_samples\_split gave the best results.

The hyperparameters, bootstrap\_list, max\_features\_list and criterion\_list was further optimized using grid search and random search in respected to our selected hyperparameters using cross validation.

After both the searches it was determined that best results are obtained when using 90 n\_estimators, 2 min\_samples\_split, 1 min\_samples\_leaf, 50 max\_depth, False bootstrap, 'sqrt' max\_features and 'entropy' criterion

When using 90 n\_estimators, 2 min\_samples\_split, 1 min\_samples\_leaf, 50 max\_depth, False bootstrap, 'sqrt' max\_features and 'entropy' criterion as hyperparameters on the default and scaled models the results are as follows.

Using the default on the features, it had 99 % accuracy, 99 % precision, 99% recall, 99 % f1 score with 0.999694146275993 % area under the curve.

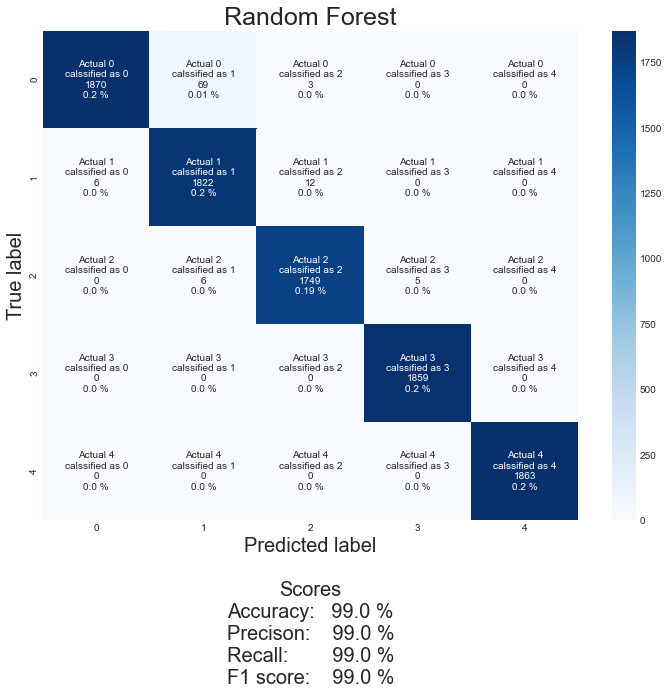


Figure 29 Random forest default

Using the standardscalar on the features, it had 99 % accuracy, 99 % precision, 99% recall, 99 % f1 score with 0.9996822954596178 % area under the curve.

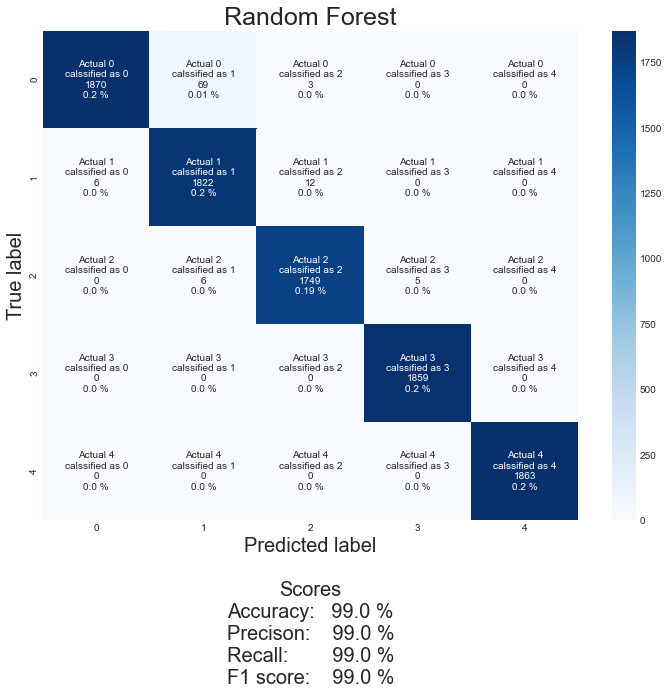


Figure 30 Random forest StandardScalar

Using the MinMaxScalar on the features, it had 99 % accuracy, 99 % precision, 99% recall, 99 % f1 score with 0.999747995347186 % area under the curve.

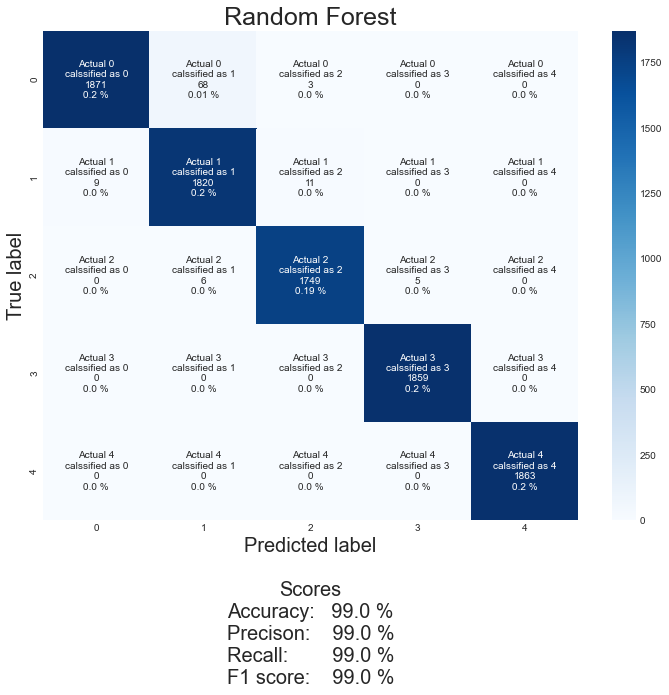


Figure 31 Random forest MinMaxScalar

Using the RobustScalar on the features, it had 99 % accuracy, 99 % precision, 99% recall, 99 % f1 score with 0.9996979450769103 % area under the curve.



Figure 32 Random forest RobustScalar

Using the Normalizer on the features, it had 99 % accuracy, 99 % precision, 99% recall, 99 % f1 score with 0.9997492068811304 % area under the curve.

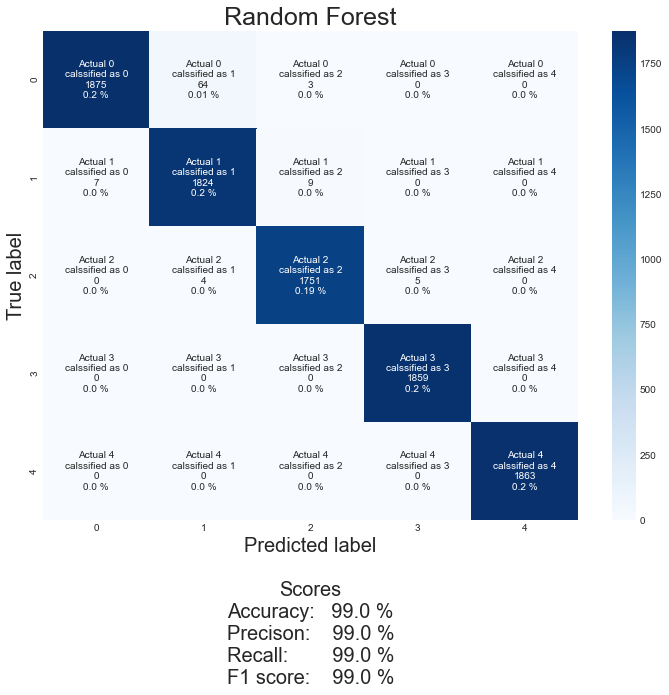


Figure 33 Random forest Normalizer

When using 90 n\_estimators, 2 min\_samples\_split, 1 min\_samples\_leaf, 50 max\_depth, False bootstrap, 'sqrt' max\_features and 'entropy' criterion as hyperparameters all the scaling techniques give , it had 99 % accuracy, 99 % precision, 99% recall, 99 % f1 score with MinMaxScalar has the best area under the curve is achieved so it is selected as the best scaling technique.

After cross validation of these results with the default results.

The defaults model results were 94.79 % with 1.28 % standard deviation.

The results after using minmax scaler with hyperparameter optimization were 94.79 % with 1.16 standard deviation.

### Decision Tree

#### Decision Tree with hyperparameters optimized

Decision Tree max\_depth hyperparameters were tuned using cross validation in a given range of numbers.

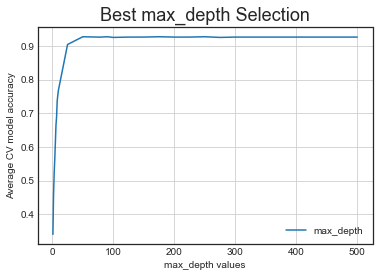


Figure 34 Decision Tree with cross validation 1

Decision Tree min\_samples\_leaf hyperparameters were tuned using cross validation in a given range of numbers.

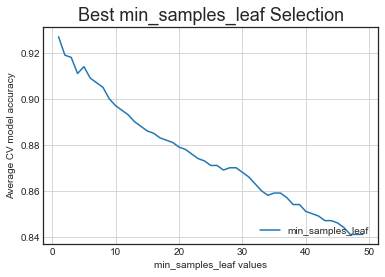


Figure 35 Decision Tree with cross validation 2

Decision Tree min\_samples\_split hyperparameters were tuned using cross validation in a given range of numbers.

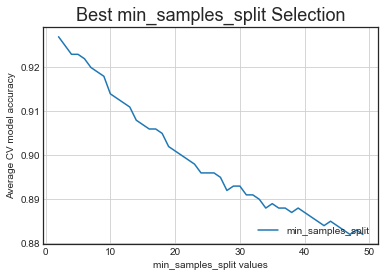


Figure 36 Decision Tree with cross validation 3

Decision Tree min\_weight\_fraction\_leaf hyperparameters were tuned using cross validation in a given range of numbers.



Figure 37 Decision Tree with cross validation 4

Decision Tree max\_leaf\_nodes hyperparameters were tuned using cross validation in a given range of numbers.

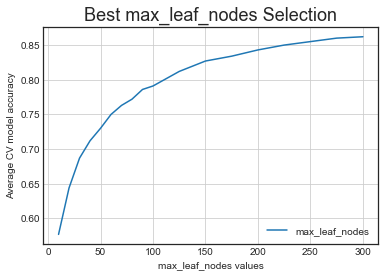


Figure 38 Decision Tree with cross validation 5

Decision Tree criterion hyperparameters were tuned using cross validation in a given range of numbers.

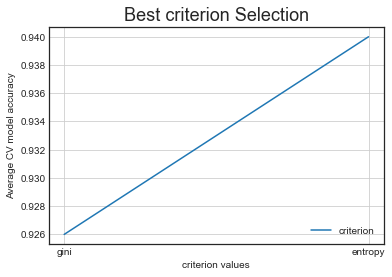


Figure 39 Decision Tree with cross validation 6

Decision Tree max\_features hyperparameters were tuned using cross validation in a given range of numbers.

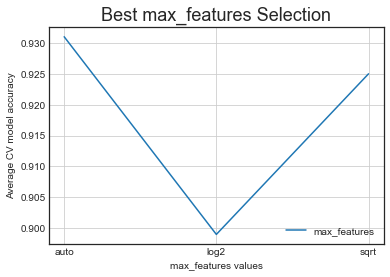


Figure 40 Decision Tree with cross validation 7

Decision Tree splitter hyperparameters were tuned using cross validation in a given range of numbers.

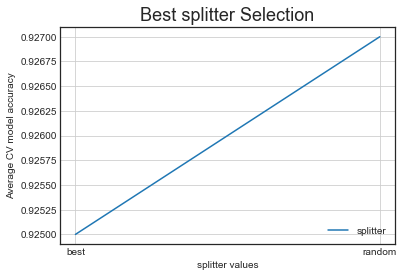


Figure 41 Decision Tree with cross validation 8

After which the hyperparameters max\_depth and splitter further tuned using grid search and random search.

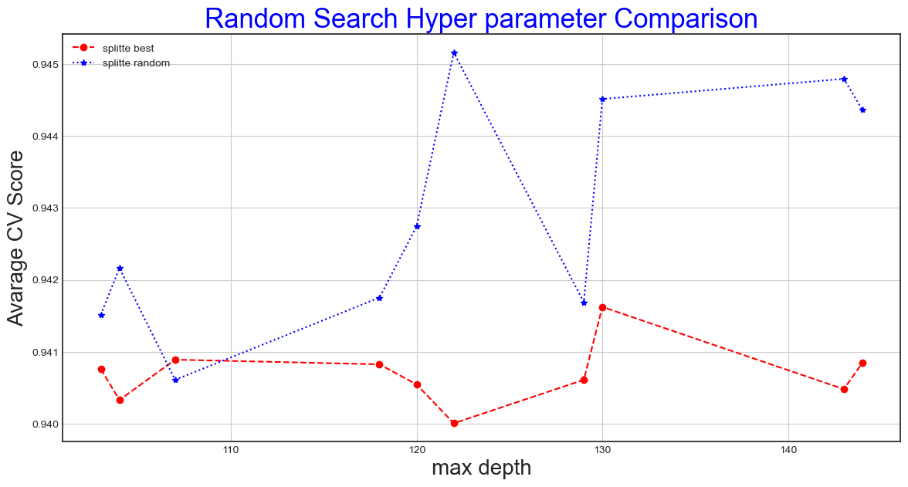


Figure 42 Decision Tree with Random Search

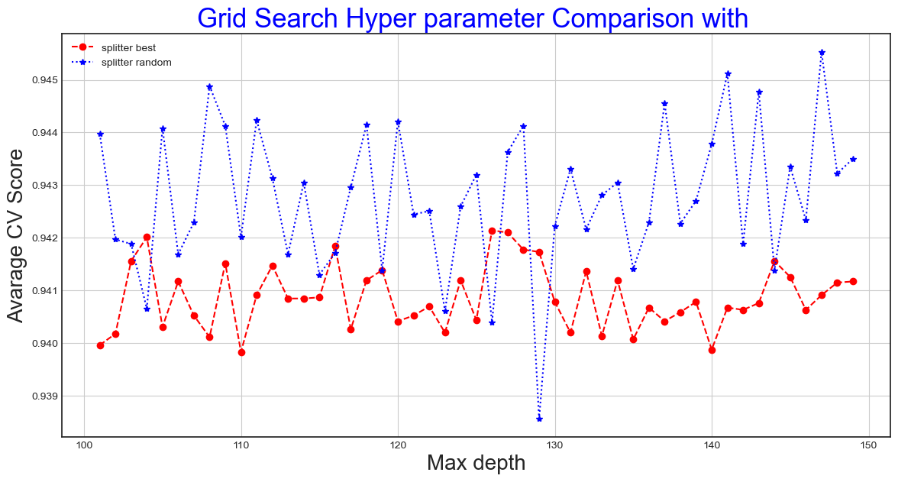


Figure 43 Decision Tree with Grid Search

After both the grid and random search it is concluded that with 1 min\_samples\_leaf ,2 min\_samples\_split , None max\_leaf\_nodes , 0.0 min\_weight\_fraction\_leaf , 'entropy' criterion, None max\_features, 121 max\_depth, 'random' splitter best results are obtained. These hyperparameters are now tested with the default unscaled oversampled features as well as these features after scaling. The results from these tests are as follows.

Using the default features, it had 99 % accuracy, 99 % precision, 99% recall, 99 % f1 score with 0.9923048031499204 % area under the curve.

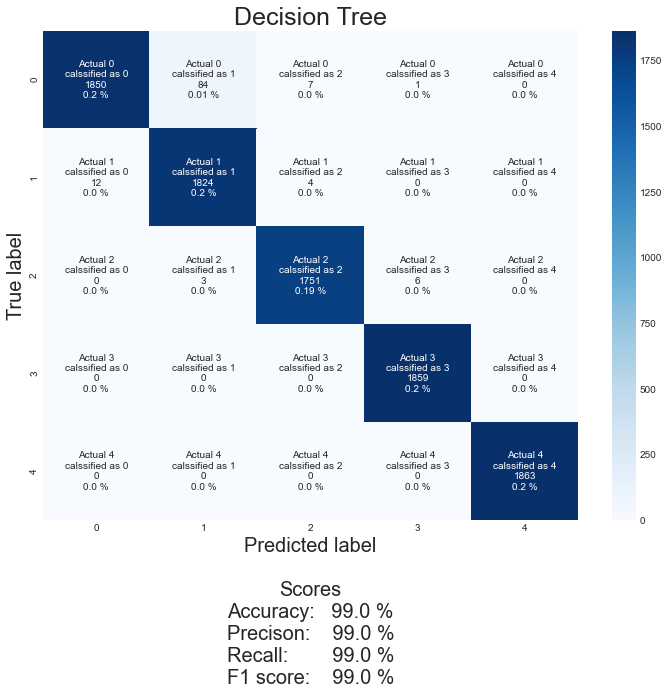


Figure 44 Decision Tree Default

Using the standardscalar on the features, it had 99 % accuracy, 99 % precision, 99% recall, 99 % f1 score with 0.9923429315411422 % area under the curve.

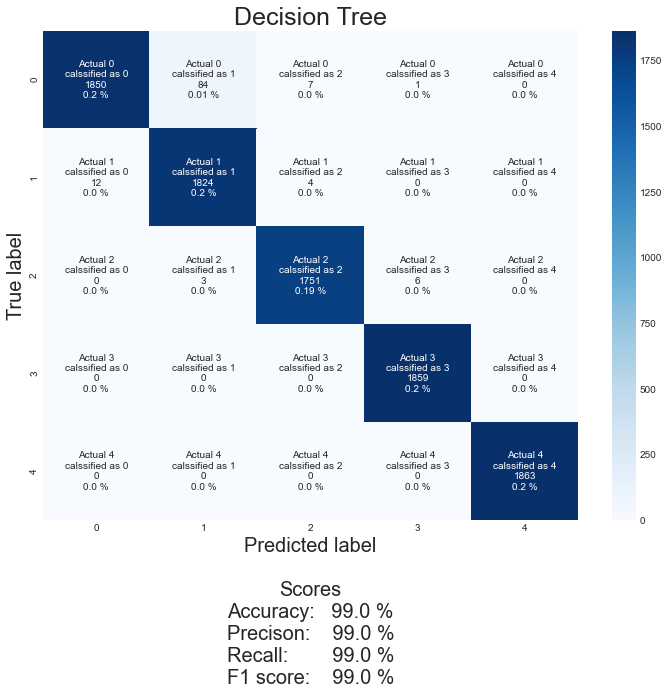


Figure 45 Decision Tree StandardScalar

Using the MinMaxScalar on the features, it had 99 % accuracy, 99 % precision, 99% recall, 99 % f1 score with 0.9918932369968839 % area under the curve.

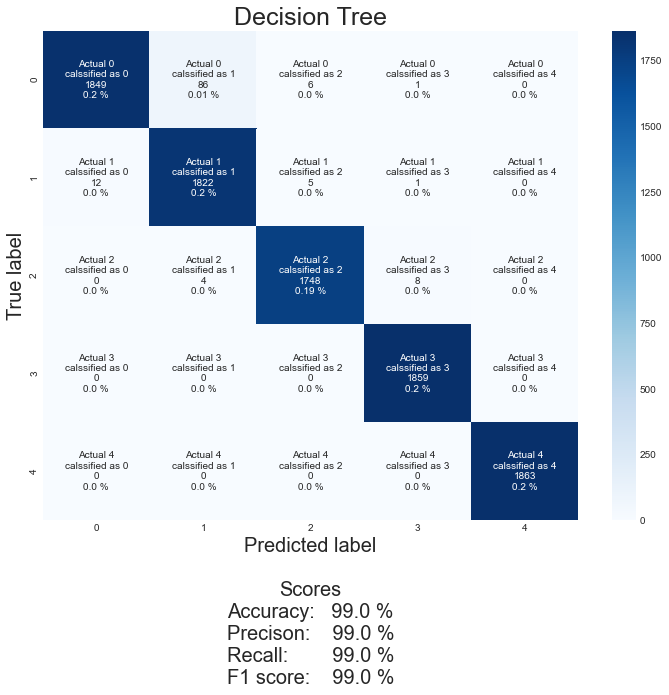
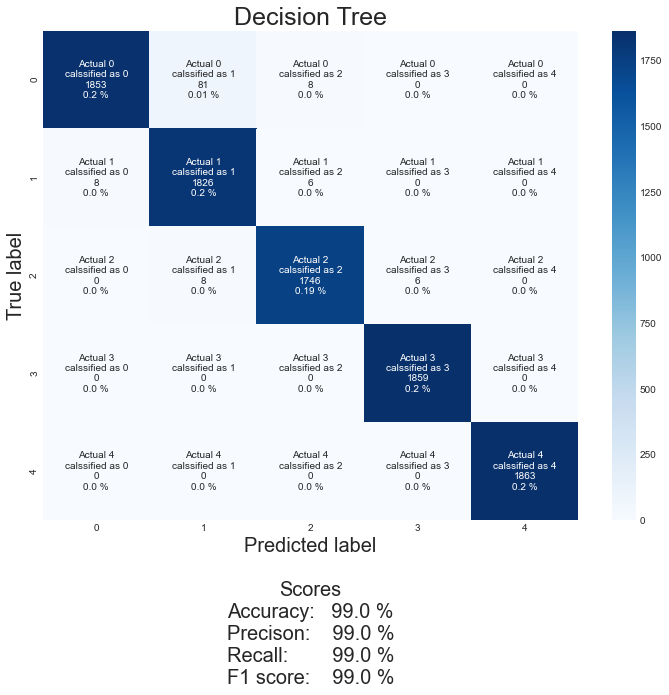
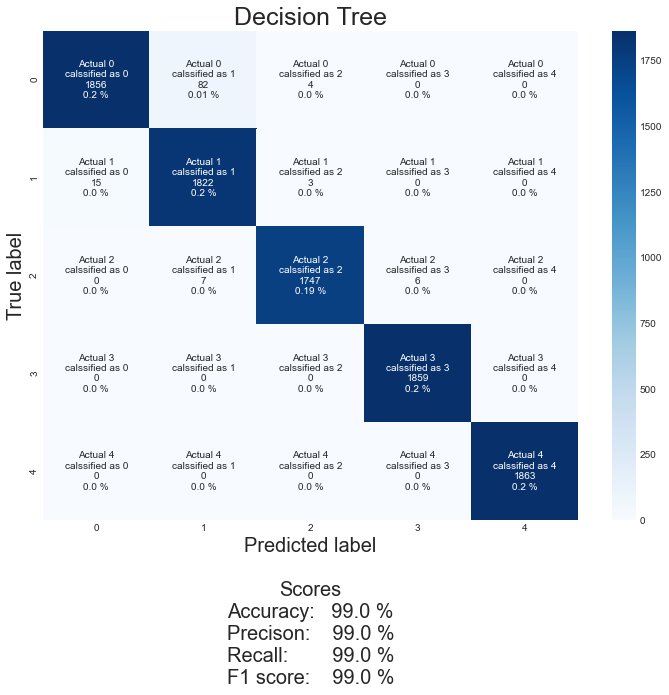


Figure 46 Decision Tree MinMaxScalar

Using the RobustScalar on the features, it had 99 % accuracy, 99 % precision, 99% recall, 99 % f1 score with 0.9922851037488755 % area under the curve.



Using the Normalizer on the features, it had 99 % accuracy, 99 % precision, 99% recall, 99 % f1 score with 0.9922766918315912 % area under the curve.



with 1 min\_samples\_leaf ,2 min\_samples\_split , None max\_leaf\_nodes , 0.0 min\_weight\_fraction\_leaf , 'entropy' criterion, None max\_features, 121 max\_depth, 'random' splitter as hyperparameters all the scaling techniques give 99 % accuracy, 99 % precision, 99% recall, 99 % f1 score with MinMaxScalar has the best area under the curve is achieved so it is selected as the best scaling technique.

After cross validation of these results with the default results.

The defaults model results were 93.11 % with 0.86 % standard deviation.

The results after using minmax scaler with hyperparameter optimization were 94.44 % with 1.05 standard deviation.